APPLICATION OF AI AND ML FOR PREDICTIVE DELAY ANALYSIS IN INFRASTRUCTURE PROJECTS

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Abstract

Infrastructure projects often face delays due to poor planning, shortage of resources, design changes, coordination problems, approval issues, and other unexpected factors. These delays can increase project cost, extend completion time, and affect the overall performance of the project. Traditional delay analysis methods are useful for identifying problems, but they can be slow and may not be suitable for large and complex infrastructure projects. In this situation, Artificial Intelligence (AI) and Machine Learning (ML) provide a possible approach for predicting delays at an early stage. The present study focuses on understanding the application of AI and ML for predictive delay analysis in infrastructure projects. The study is based on a review of existing research papers and real project case studies, along with questionnaire responses collected from respondents. The study examines common causes of project delays, the effectiveness and limitations of traditional delay analysis methods, and the possible role of AI and ML in improving delay prediction and project decision-making. The findings from the case studies are also used to understand how different delay factors have affected real infrastructure projects. The results show that delays are a common problem in infrastructure projects, with poor planning and lack of resources being important contributing factors. The questionnaire findings also show a positive perception towards AI and ML, particularly for early delay prediction, data analysis, and decision-making. At the same time, some uncertainty remains regarding their practical implementation and their ability to reduce cost overruns. Overall, the study indicates that AI and ML have strong potential to support predictive delay analysis and improve project management. However, better data availability, technical knowledge, and practical implementation are required for their wider use in infrastructure projects.

Keywords: Artificial Intelligence, Machine Learning, Infrastructure Projects, Project Delays, Predictive Analysis, Delay Management, Construction Management

1. INTRODUCTION

Background of Infrastructure Project Delays

Infrastructure development plays an important role in the economic and social development of a country. Projects such as highways, bridges, railways, airports, metro systems, and other public infrastructure improve connectivity, transportation, and access to essential services. In countries such as India, rapid urbanization, population growth, and industrial development have increased the need for large infrastructure projects. However, the increasing size and complexity of these projects also create several management challenges, among which project delay is one of the most common.

Infrastructure project delays can occur because of poor planning, shortage of labour and materials, financial problems, design changes, technical difficulties, approval issues, weather conditions, and poor coordination among stakeholders. These factors may occur individually or at the same time, making it difficult to identify the exact reason for a delay. Delays can result in time overruns, increased project costs, reduced productivity, contractual disputes, and difficulties in achieving planned project objectives. Therefore, identifying delay factors at an early stage is important for effective project management.

Traditionally, delays have been analyzed using methods such as project schedules, Critical Path Method (CPM), progress monitoring, and expert judgment. These methods are useful and continue to be used in construction practice. However, they can become time-consuming when projects involve a large number of activities and different sources of information. Traditional approaches are also mainly used to understand and assess delays after problems have occurred. This creates a need for methods that can provide earlier information about possible project delays.

Application of AI and ML in Predictive Delay Analysis

The development of Artificial Intelligence (AI) and Machine Learning (ML) has created new possibilities for predictive delay analysis. AI allows computer systems to perform tasks that normally require human intelligence, while ML enables systems to learn patterns from available data and use them for prediction. In infrastructure projects, these technologies can analyze historical project information related to schedule, resources, cost, weather, and other project conditions. Based on these patterns, AI and ML can help identify activities or conditions that may increase the risk of delay.

Recent research has shown growing interest in the use of machine learning for construction delay prediction. Sahu et al. (2025) examined supervised machine learning approaches for construction delay prediction and reported strong performance from models such as Random Forest and XGBoost. Neththikumara et al. (2025) also showed that machine learning can be used to study concurrent delays involving factors such as labour, resources, weather, and project complexity. Similarly, Shyam and Tiwari (2025) discussed the use of Machine Learning and Multi-Criteria Decision Analysis for identifying and prioritizing delay factors. These studies indicate that data-based methods can provide useful support for understanding and predicting project delays.

At the same time, the practical use of AI and ML is not free from challenges. Their effectiveness depends on the availability of reliable and properly organized project data. Lack of technical knowledge, implementation cost, data quality, and difficulty in integrating new technologies with existing project management systems can also limit their use. In addition, much of the existing research focuses on technical model development and algorithm performance. There is therefore a need for a clearer understanding of how the findings from such studies relate to actual infrastructure project delays and traditional delay management practices.

Purpose and Focus of the Present Study

The present study focuses on the application of Artificial Intelligence and Machine Learning for predictive delay analysis in infrastructure projects. The study reviews existing research and real project case studies to understand the major causes of delays and the potential role of AI and ML in identifying such risks at an early stage. It also considers the differences between traditional delay analysis and AI/ML-based approaches, along with their major benefits and practical challenges.

Overall, the study aims to provide a simple and practical understanding of how AI and ML can support better delay analysis in infrastructure projects. By connecting findings from previous research with real project experiences, the study seeks to explain the potential of predictive approaches for improving project planning, decision-making, and timely project completion.

2. REVIEW OF LITERATURE

Shyam and Tiwari (2025) reviewed the use of Machine Learning (ML) and Multi-Criteria Decision Analysis (MCDA) for construction delay management. The study found that ML can help predict delay factors using past project data, while MCDA can help identify and rank the most important causes. The study shows that combining prediction with proper decision-making can improve delay management and project planning.

Sahu et al. (2025) studied supervised machine learning methods for predicting construction delays. Their findings showed that Random Forest and XGBoost performed better than simpler models in predicting delays. The study also explained that early prediction can help project managers take corrective action before delays become serious. However, data quality and proper system integration remain important challenges.

Neththikumara et al. (2025) examined concurrent delays, where several delay factors occur together. The study used K-means clustering and Random Forest to identify patterns in factors such as labour, resources, weather, and project complexity. The findings showed that ML can handle complex relationships between different delay factors and provide useful predictive information.

Amaldev et al. (2025) reviewed major causes of infrastructure project delays. Poor planning, weak communication, resource problems, regulatory changes, and environmental conditions were identified as important factors. The study also highlighted the need for better risk management and advanced technologies to reduce delays. These findings provide a useful base for understanding why predictive delay analysis is required.

Gondia et al. (2020) investigated ML algorithms for predicting construction delay risks. The study showed that machine learning can identify different sources of delay and understand the relationship between them. This can help project managers recognize important risks at an early stage. The research supports the use of data-based methods for improving delay risk prediction.

Khodabakhshian et al. (2024) studied the application of ML in predicting construction delays and cost overruns. Different techniques, including Decision Trees, Neural Networks, and Gradient Boosting, were examined. The findings showed that ML can improve risk prediction in complex projects. The study also highlights the connection between delay and cost performance.

Egwim et al. (2021) examined the application of AI for predicting construction project delays. The study considered factors such as project size, complexity, and resource availability. The findings showed that AI can help identify factors related to delays and improve prediction. However, the authors also highlighted that reliable and sufficient data are necessary for effective AI-based analysis.

Chauhan (2025) studied the use of AI and ML for construction scheduling and risk management. The study found that predictive analysis and optimization can improve completion-time forecasting and project planning. AI-based tools can also support better decision-making and risk identification. These findings show that predictive technologies can be useful for improving overall project management.

Zhang and Li (2023) compared different ML models for predicting construction duration. The study found that Artificial Neural Networks and Gradient Boosting Trees provided strong prediction results. Accurate duration forecasting can help improve resource allocation and reduce uncertainty in project schedules. This makes the study relevant to predictive delay analysis.

Yaseen et al. (2020) developed a hybrid AI model for predicting construction delay risks. The findings showed that hybrid AI approaches can deal with complex and uncertain project conditions and provide useful delay predictions. The study supports the use of AI for identifying risks before they seriously affect project performance.

Amuna et al. (2026) examined predictive analytics for improving construction and infrastructure project delivery. The study found that ML and hybrid approaches can support better prediction of project risks and delays. However, poor data systems and difficulties in integrating new technologies can limit practical use. This highlights the gap between the technical potential of AI and its actual implementation.

Gajera (2024) examined AI-driven analytics using SmartPM for predicting and managing schedule delays in complex infrastructure projects. The study showed that AI-based analytics can provide early information about possible schedule problems and help managers take corrective action. This provides a practical example of how predictive technology can support infrastructure project management.

Ghosh (2022) studied AI-based predictive maintenance in the manufacturing sector. Although the study was not directly related to construction, it showed how AI can predict equipment-related problems and improve operational efficiency. This idea is relevant to infrastructure projects because equipment problems can interrupt construction activities and contribute to delays.

Yildirim and Din (2026) examined construction project delays using different machine learning techniques. The study focused on identifying and assessing several delay factors using models such as SVM, ANN, and KNN. The findings showed that ML can help identify important risk factors and support better project decisions. This is useful because understanding the causes of delay is important for taking preventive action.

Katuri and Divya (2025) studied ML-based cost forecasting in Indian highway projects. Although the main focus was cost prediction, the study is relevant because cost and time performance are closely connected in infrastructure projects. The findings showed that ML can improve forecasting and support better financial planning. This can indirectly help in reducing problems that may contribute to project delays.

Overall, the reviewed studies show that AI and ML have growing potential in construction and infrastructure delay analysis. Existing research has mainly focused on predicting delays, identifying important risk factors, improving scheduling, and supporting project decisions. At the same time, issues such as data quality, technical knowledge, cost, and system integration remain important challenges. These findings provide the basis for examining how AI and ML can support predictive delay analysis in infrastructure projects through previous research and real project case studies.

3. OBJECTIVE OF THE STUDY

- To study the common reasons behind delays in infrastructure projects and understand how AI and ML are being used to address them.
- To explore different AI and ML techniques that are currently applied for predicting delays in construction projects.
- To compare traditional delay analysis methods with AI and ML-based approaches.
- To identify the practical benefits and challenges of using AI and ML for predictive delay analysis in infrastructure projects.

4. METHODOLOGY

Research Design

The study follows an analytical mixed-method research design to examine the application of Artificial Intelligence (AI) and Machine Learning (ML) in predictive delay analysis for infrastructure projects. Both primary and secondary data are considered to develop a practical understanding of project delays, their major causes, and the possible use of AI and ML for early prediction.

Data Sources and Collection

The study uses both primary and secondary sources of data. Primary data will be collected through a structured questionnaire prepared using a five-point Likert scale. The questionnaire focuses on common causes of infrastructure project delays, traditional delay analysis methods, awareness of AI and ML, and their perceived effectiveness in predicting and managing delays. A total of 200 questionnaires were distributed, out of which 110 valid responses were obtained and considered for analysis.

Secondary data will be collected from published research papers, academic journals, government and institutional reports, and previously published infrastructure project case studies. A 17-18 research papers and 8 case studies are considered to support the analysis and discussion.

Sampling Technique

Purposive sampling is used for the primary survey. Respondents are selected based on their knowledge or experience related to construction and infrastructure projects. This approach helps obtain responses from participants who are more familiar with project delays and construction management practices.

Variables Considered

The study considers major project delay factors such as poor planning, financial issues, labour shortage, material delays, equipment failure, weather conditions, and design changes as independent variables. Project delay or time overrun is considered the main dependent variable. These factors are examined to understand their perceived relationship with infrastructure project delays.

Data Analysis

The primary data is analyzed using frequency and percentage analysis, mean score analysis, and ranking methods. Tables, bar charts, and pie charts are used to present the responses in an easy-to-understand form. The secondary data is examined through literature review and comparative analysis to identify major findings from previous studies and case studies.

5. DATA ANALYSIS

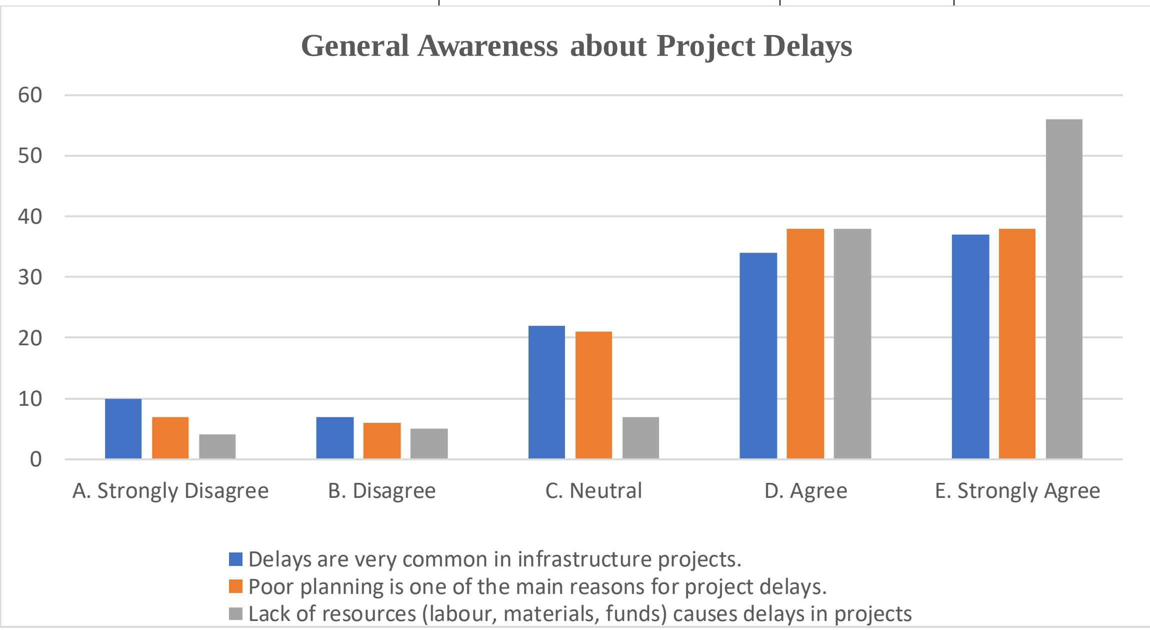
This section presents the analysis of the primary data collected from **110 respondents**. The responses were obtained through a structured questionnaire related to infrastructure project delays, traditional delay analysis methods, and the application of Artificial Intelligence (AI) and Machine Learning (ML). The questionnaire used a five-point response scale ranging from **Strongly Disagree to Strongly Agree**.

The data has been presented section-wise using frequency and percentage analysis. The purpose of this analysis is to understand the opinions of respondents regarding the common causes of project delays, the effectiveness and limitations of traditional methods, and the perceived role of AI and ML in predictive delay analysis.

General Awareness about Project Delays

Question	**Response Option**	**Frequency**	**Percentage (%)**
1. Delays are very common in infrastructure projects.	A. Strongly Disagree	10	9.1
	B. Disagree	7	6.4
	C. Neutral	22	20.0

	D. Agree	34	30.9
	E. Strongly Agree	37	33.6
	Total	**110**	**100.0**
2. Poor planning is one of the main reasons for project delays.	A. Strongly Disagree	7	6.4
	B. Disagree	6	5.5
	C. Neutral	21	19.1
	D. Agree	38	34.5
	E. Strongly Agree	38	34.5
	Total	**110**	**100.0**
3. Lack of resources (labour, materials, funds) causes delays in projects.	A. Strongly Disagree	4	3.6
	B. Disagree	5	4.5
	C. Neutral	7	6.4
	D. Agree	38	34.5
	E. Strongly Agree	56	50.9
	Total	**110**	**100.0**



The results show that infrastructure project delays are widely recognized by the respondents. For the first statement, **33.6% strongly agreed** and **30.9% agreed** that delays are very common, giving a combined positive response of **64.5%**. A further **20.0%** of respondents remained neutral, while **6.4% disagreed** and **9.1% strongly disagreed**. This indicates that nearly two-thirds of the respondents consider project delays to be a common problem in infrastructure development.

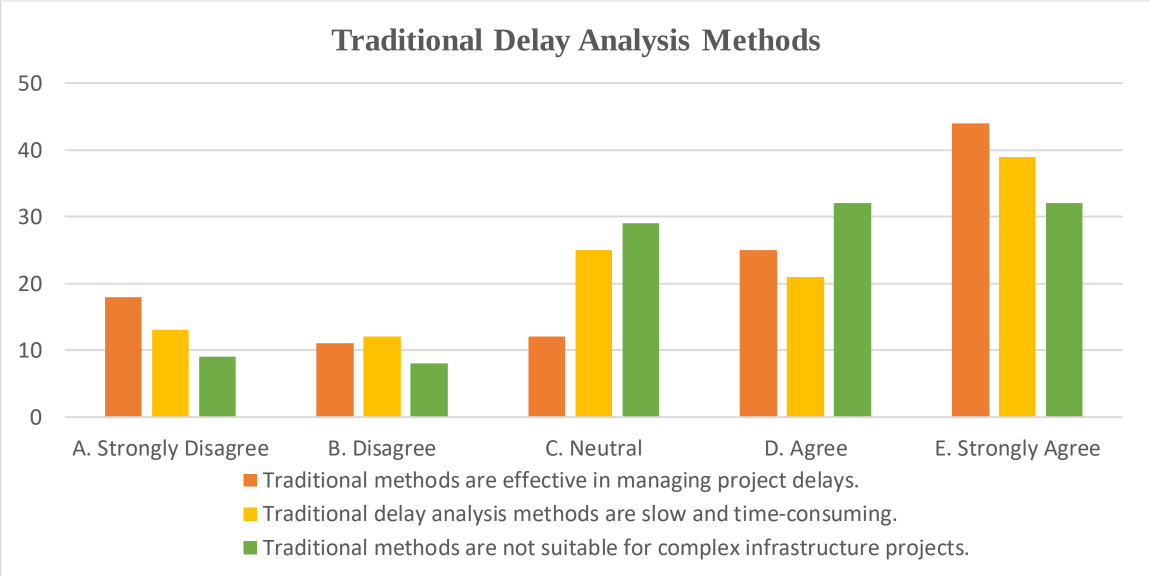
Poor planning was also identified as an important reason for delays. **34.5% agreed** and **34.5% strongly agreed**, resulting in a combined agreement of **69.0%**. Meanwhile, **19.1%**

were neutral, **5.5% disagreed**, and **6.4% strongly disagreed**. The responses therefore indicate that most respondents associate ineffective planning with delays in infrastructure projects.

The strongest response in this section was related to the lack of resources. **50.9% strongly agreed** and **34.5% agreed** that shortages of labour, materials, and funds cause project delays. Together, these responses represent **85.4%** of the respondents. Only **6.4%** were neutral, while **4.5% disagreed** and **3.6% strongly disagreed**. Overall, the findings show that resource availability is perceived as a particularly important factor affecting timely project completion.

Traditional Delay Analysis Methods

Question	**Response Option**	**Frequency**	**Percentage (%)**
4. Traditional methods are effective in managing project delays.	A. Strongly Disagree	18	16.4
	B. Disagree	11	10.0
	C. Neutral	12	10.9
	D. Agree	25	22.7
	E. Strongly Agree	44	40.0
	Total	**110**	**100.0**
5. Traditional delay analysis methods are slow and time-consuming.	A. Strongly Disagree	13	11.8
	B. Disagree	12	10.9
	C. Neutral	25	22.7
	D. Agree	21	19.1
	E. Strongly Agree	39	35.5
	Total	**110**	**100.0**
6. Traditional methods are not suitable for complex infrastructure projects.	A. Strongly Disagree	9	8.2
	B. Disagree	8	7.3
	C. Neutral	29	26.4
	D. Agree	32	29.1
	E. Strongly Agree	32	29.1
	Total	**110**	**100.0**



The responses indicate that traditional delay analysis methods are still considered useful by a considerable proportion of respondents. For the statement on their effectiveness, **40.0% strongly agreed** and **22.7% agreed**, giving a combined positive response of **62.7%**. In comparison, **10.9%** remained neutral, while **10.0% disagreed** and **16.4% strongly disagreed**. Thus, the findings do not suggest that traditional methods are completely ineffective; rather, they continue to have practical value for many respondents.

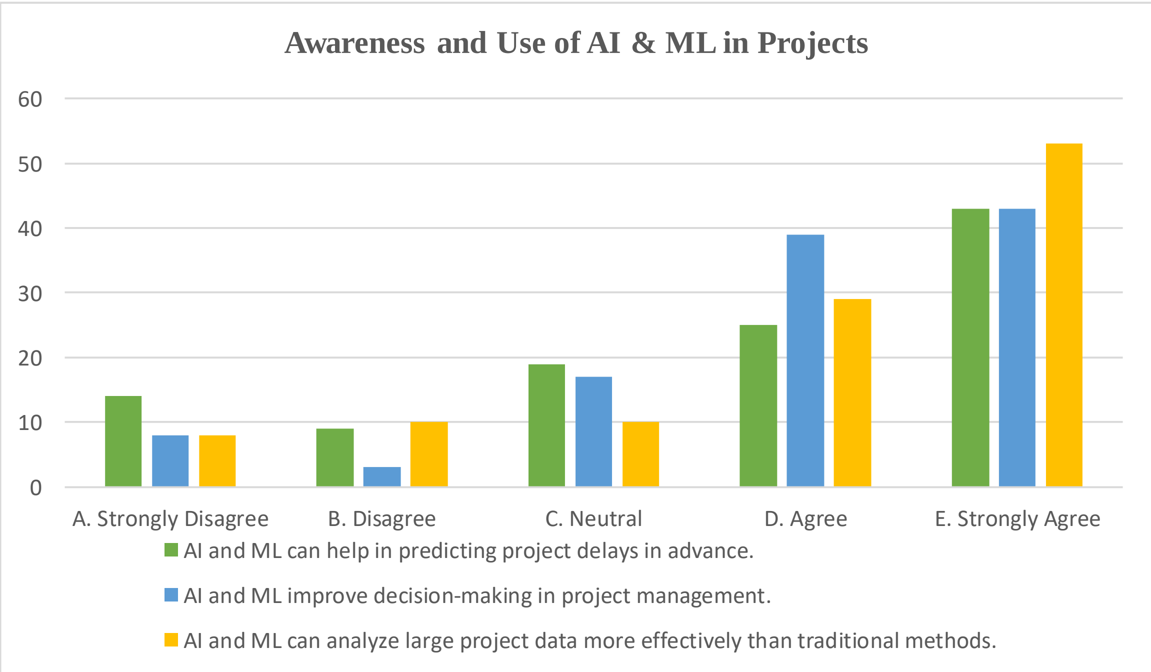
At the same time, more than half of the respondents considered traditional delay analysis methods to be slow and time-consuming. **35.5% strongly agreed** and **19.1% agreed**, resulting in **54.6% agreement**. **22.7%** were neutral, while **10.9% disagreed** and **11.8% strongly disagreed**. This shows that although traditional methods are still used, their time requirements may be a concern when projects become more complicated.

Regarding their suitability for complex infrastructure projects, **29.1% agreed** and **29.1% strongly agreed**, giving a combined response of **58.2%**. However, **26.4%** were neutral, while **7.3% disagreed** and **8.2% strongly disagreed**. The results suggest that a majority see limitations in applying traditional methods to complex projects. Overall, the responses indicate a mixed position: traditional methods retain their usefulness, but their speed and suitability for highly complex projects may be limited.

Awareness and Use of AI & ML in Projects

Question	Response Option	Frequency	Percentage (%)
7. AI and ML can help in predicting project delays in advance.	A. Strongly Disagree	14	12.7
	B. Disagree	9	8.2
	C. Neutral	19	17.3
	D. Agree	25	22.7
	E. Strongly Agree	43	39.1

	Total	**110**	**100.0**
8. AI and ML improve decision-making in project management.	A. Strongly Disagree	8	7.3
	B. Disagree	3	2.7
	C. Neutral	17	15.5
	D. Agree	39	35.5
	E. Strongly Agree	43	39.1
	Total	**110**	**100.0**
9. AI and ML can analyze large project data more effectively than traditional methods.	A. Strongly Disagree	8	7.3
	B. Disagree	10	9.1
	C. Neutral	10	9.1
	D. Agree	29	26.4
	E. Strongly Agree	53	48.2
	Total	**110**	**100.0**



The findings show a generally positive perception of AI and ML among the respondents. For the ability of AI and ML to predict project delays in advance, **39.1% strongly agreed** and **22.7% agreed**, giving a combined positive response of **61.8%**. Meanwhile, **17.3%** were neutral, **8.2% disagreed**, and **12.7% strongly disagreed**. The result indicates that most respondents believe AI and ML can provide useful support for identifying possible delays before they occur.

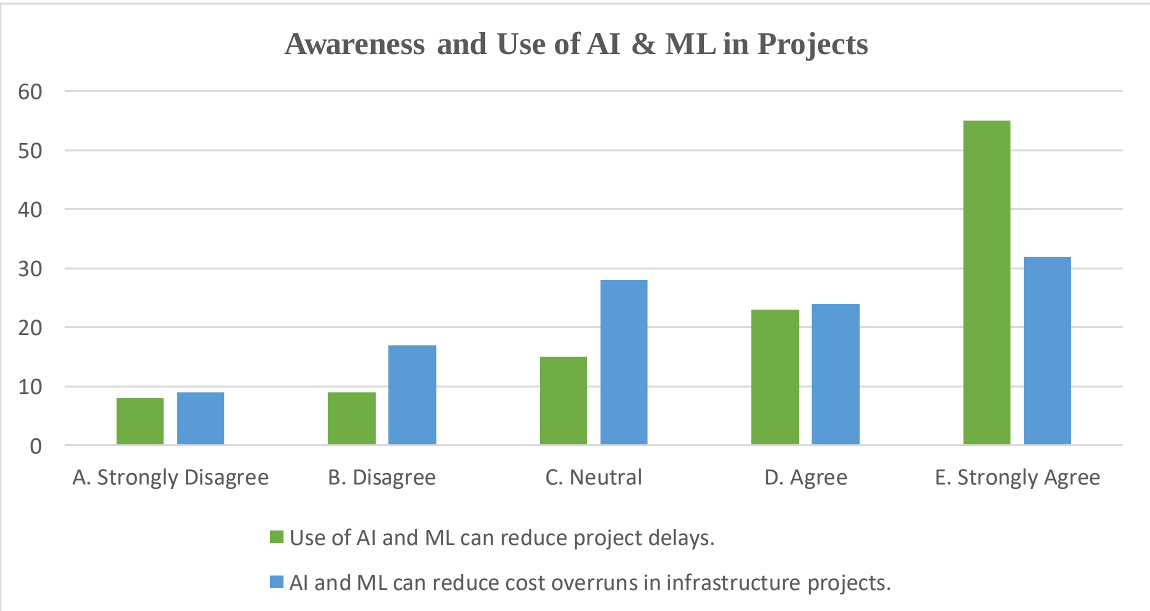
The perception is stronger regarding decision-making. **39.1% strongly agreed** and **35.5% agreed** that AI and ML improve project management decision-making, resulting in a combined agreement of **74.6%**. Only **2.7% disagreed** and **7.3% strongly disagreed**, while

15.5% remained neutral. This suggests that respondents see AI and ML as useful sources of information for supporting project managers in making timely and informed decisions.

The ability to analyze large project datasets also received strong support. **48.2% strongly agreed** and **26.4% agreed**, producing a combined positive response of **74.6%**. In contrast, **9.1%** were neutral, **9.1% disagreed**, and **7.3% strongly disagreed**. Overall, the responses indicate that AI and ML are viewed positively, particularly for handling large amounts of project information and supporting decision-making. Their ability to predict delays in advance also received majority support, although some respondents remain uncertain about their practical use.

Impact and Effectiveness of AI & ML

Question	Response Option	Frequency	Percentage (%)
10. Use of AI and ML can reduce project delays.	A. Strongly Disagree	8	7.3
	B. Disagree	9	8.2
	C. Neutral	15	13.6
	D. Agree	23	20.9
	E. Strongly Agree	55	50.0
	Total	**110**	**100.0**
11. AI and ML can reduce cost overruns in infrastructure projects.	A. Strongly Disagree	9	8.2
	B. Disagree	17	15.5
	C. Neutral	28	25.5
	D. Agree	24	21.8
	E. Strongly Agree	32	29.1
	Total	**110**	**100.0**



The findings show strong support for the potential of AI and ML to reduce project delays. Half of the respondents (**50.0%**) strongly agreed with this statement, while **20.9%** agreed, resulting in a combined positive response of **70.9%**. A further **13.6%** were neutral, whereas **8.2% disagreed** and **7.3% strongly disagreed**. The result indicates that most respondents believe predictive technologies can contribute to better project control and may help identify potential delay risks at an earlier stage.

The responses regarding cost overruns are more mixed. **29.1% strongly agreed** and **21.8% agreed** that AI and ML can reduce cost overruns, giving a combined positive response of **50.9%**. However, **25.5%** remained neutral, while **15.5% disagreed** and **8.2% strongly disagreed**. The relatively high neutral response suggests that respondents are less certain about the direct relationship between AI/ML use and cost reduction. Therefore, the data provides stronger support for the role of AI and ML in delay reduction than for their direct impact on cost overruns.

6. ANALYSIS OF CASE STUDIES

The eight case studies show that delays in infrastructure projects are generally caused by a combination of technical, managerial, financial, land-related, and operational factors. The cases also show that the nature of delay changes according to the type and complexity of the project. These findings are useful for understanding where AI and ML-based predictive delay analysis can support infrastructure project management.

Case Study 1: Delhi Metro Phase III, India

Major Delay Issues: The Delhi Metro Phase III case shows the difficulty of managing a large project involving tunnels, stations, signalling, electrical systems, and several agencies. Unforeseen technical and coordination-related issues created pressure on the project schedule.

Analysis: The case shows that continuous monitoring is important in large infrastructure projects. AI and ML could help analyze previous project progress, contractor performance, and site-related data to identify activities with a higher possibility of delay.

Key Finding: Better prediction of project risks can support early action, resource planning, and timely decision-making.

Case Study 2: Pune Metro Rail Project, India

Major Delay Issues: Land acquisition and compensation-related issues were important reasons for delay in the Pune Metro project. Difficulties in completing the land acquisition process affected the timely start of project work.

Analysis: This case shows that delays can occur even before major construction activities begin. AI and ML could potentially analyze land status, pending approvals, compensation issues, and stakeholder-related information to identify high-risk areas.

Key Finding: Early identification of land-related risks can help project authorities take corrective action before they affect the construction schedule.

Case Study 3: Mumbai Metro Line 3, India

Major Delay Issues: Mumbai Metro Line 3 faced problems related to land, planning decisions, the car shed issue, and the complexity of underground construction. These factors affected the planned completion schedule and increased project costs.

Analysis: The case shows how different delay factors can occur together. AI and ML can potentially combine information related to land acquisition, approvals, design changes, and construction progress to identify possible delay risks.

Key Finding: Predictive analysis can be useful when a project has several connected risks rather than one clearly identifiable cause.

Case Study 4: Mumbai Coastal Road Project, India

Major Delay and Risk Issues: The Mumbai Coastal Road Project faced issues related to design changes, construction quality, safety testing, and cost escalation. The change in the Worli bridge navigation span also resulted in additional cost.

Analysis: This case shows that design decisions and quality-related issues can have a wider effect on project performance. AI and ML could be used to study design changes, inspection reports, project progress, and previous risk patterns to identify areas requiring greater attention.

Key Finding: Predictive analysis should consider not only project time but also design, quality, safety, and cost-related risks.

Case Study 5: Bengaluru Metro Yellow Line, India

Major Delay Issues: The Bengaluru Metro Yellow Line experienced delays related to land acquisition, the COVID-19 pandemic, and late delivery of rolling stock. These factors affected the final opening of the line.

Analysis: This case shows that infrastructure delays can come from different stages of a project, including land, procurement, external events, and commissioning. AI and ML could help combine these different sources of information and identify possible schedule risks.

Key Finding: Predictive models can support better planning by considering several delay factors together rather than analyzing them separately.

Case Study 6: Crossrail Project, London

Major Delay Issues: The Crossrail project faced major challenges during systems integration, testing, signalling, software development, and commissioning. The problems affected the planned opening and created additional cost and schedule pressure.

Analysis: This case shows that physical construction completion does not always mean that an infrastructure project is ready for operation. AI and ML could potentially analyze testing progress, system readiness, software issues, and commissioning data to identify possible delays.

Key Finding: Predictive delay analysis should also consider technical systems and integration activities, particularly in modern infrastructure projects.

Case Study 7: Boston Big Dig Project, USA

Major Delay Issues: The Boston Big Dig experienced serious problems related to unrealistic estimates, complex site conditions, design changes, utilities, environmental issues, and construction risks. These factors contributed to major time and cost increases.

Analysis: The case highlights the importance of identifying risks during the early planning stage. Historical project data, site information, design changes, and previous risk records could potentially be analyzed using AI and ML to identify high-risk activities.

Key Finding: Predictive analysis can help project managers understand possible risks before they develop into major schedule and cost problems.

Case Study 8: Heathrow Terminal 5, UK

Major Delay and Operational Issues: Heathrow Terminal 5 faced serious problems during its opening, particularly with baggage systems, staff familiarisation, software systems, passenger movement, and contingency arrangements.

Analysis: This case shows that project success depends not only on physical construction but also on operational readiness. AI and ML could potentially analyze system testing, staff readiness, software performance, and operational information before project opening.

Key Finding: Predictive delay analysis should cover both construction activities and the final operational stage of complex infrastructure projects.

7. RESULTS AND DISCUSSION

This section presents the main findings of the study based on the responses of **110 respondents** and the analysis of **eight infrastructure project case studies**. The results focus on the major causes of project delays, the limitations of traditional delay analysis, and the possible role of AI and ML in predicting and managing delays.

The questionnaire results show that infrastructure project delays are a common concern. **64.5%** of respondents agreed or strongly agreed that delays are common, while **69.0%** identified poor planning as an important cause. The strongest response was related to resources, with **85.4%** agreeing or strongly agreeing that lack of labour, materials, and funds can cause delays. The case studies support these findings. Delhi Metro Phase III showed technical and coordination challenges, Pune Metro highlighted land acquisition and compensation issues, while Mumbai Metro Line 3 involved land, planning, and construction-related difficulties.

The case studies also show that delay factors differ according to the type of infrastructure project. The Mumbai Coastal Road Project highlighted design changes, quality, safety, and cost-related issues, while the Bengaluru Metro Yellow Line was affected by land acquisition, the COVID-19 pandemic, and rolling-stock supply. In the international cases, Crossrail mainly showed problems with system integration, testing, signalling, and commissioning. The Boston Big Dig highlighted complex site conditions, design changes, utilities, and unrealistic estimates, whereas Heathrow Terminal 5 showed problems related to baggage systems, staff readiness, software, and operational planning. Together, these cases show that infrastructure delays usually result from several connected factors rather than one single cause.

The findings on traditional delay analysis show a mixed response. **62.7%** of respondents agreed or strongly agreed that traditional methods are effective, but **54.6%** considered them slow and time-consuming. Also, **58.2%** felt that traditional methods are not suitable for complex infrastructure projects. The case studies support this concern because projects such as Crossrail and the Boston Big Dig involved many interconnected risks that were difficult to manage through conventional monitoring alone.

The responses towards AI and ML were generally positive. **61.8%** agreed or strongly agreed that AI and ML can help predict project delays in advance. Further, **74.6%** believed that AI and ML can improve project management decision-making, while **74.6%** agreed that they can analyze large project data more effectively than traditional methods. The case studies show several areas where such predictive analysis could be useful, including land acquisition in Pune Metro, supply and procurement risks in Bengaluru Metro, system testing in Crossrail, and operational readiness in Heathrow Terminal 5.

The results also show that **70.9%** of respondents agreed or strongly agreed that AI and ML can help reduce project delays. However, the response regarding cost overruns was more moderate, with **50.9%** showing agreement. This suggests that respondents have greater confidence in AI and ML for early delay prediction and project control than for directly reducing project costs.

Overall, the questionnaire and case study findings support the potential of AI and ML as **supporting tools for predictive delay analysis**. The case studies demonstrate the practical nature of delay problems, while the survey shows that construction professionals generally recognize the value of data-based prediction. At the same time, AI and ML cannot completely replace traditional project management methods. Their usefulness will depend on reliable project data, proper implementation, and the ability of project teams to use the information for timely decision-making.

8. CONCLUSION

The study concludes that delays are a major challenge in infrastructure projects and are mainly influenced by poor planning, shortage of resources, land-related problems, design changes, and technical issues. The findings also show that traditional delay analysis methods are still useful, but they may become less effective when projects are large, complex, and involve many interconnected activities. The case studies further show that delays can arise at different stages, from planning and land acquisition to construction, system integration, and final operation. The study also indicates that AI and ML have good potential for predictive delay analysis. These technologies can help in identifying possible risks at an early stage, analyzing large amounts of project data, and supporting better decision-making. However, AI and ML cannot solve project delays on their own. Their effectiveness depends on reliable data, proper implementation, skilled professionals, and timely management action. Therefore, combining traditional project management practices with AI and ML-based tools can provide a more effective approach to infrastructure delay management.

9. FUTURE SCOPE

Future research can focus on developing actual AI and ML models using real infrastructure project data. Different algorithms can be tested and compared to identify suitable methods for predicting delays in highways, metro projects, bridges, airports, and other infrastructure projects. Larger datasets can also help improve the reliability and accuracy of predictive models.

There is also scope for developing real-time delay prediction systems using project progress, labour, material availability, weather, cost, and other project information. Such systems could provide early warnings and help project managers take corrective action before delays become serious. Further research using real project data and larger samples can help validate the findings and improve the practical use of AI and ML in infrastructure project management.

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