Leveraging AI and Automation in Research Project Planning and Execution: A Systematic Literature Review

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ABSTRACT

Artificial intelligence (AI) and automation have transformed research project management by enhancing predictive accuracy, decision-making, and resource allocation. This systematic literature review explores the application of AI-driven models and automation tools in improving research project planning and execution. Machine learning (ML) models, including Random Forest, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and XGBoost, have demonstrated improved cost estimation, scheduling, and risk assessment. Deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have enabled dynamic scheduling and real-time decision-making. Hybrid AI models, combining decision trees, genetic algorithms, fuzzy logic, and Bayesian networks, have enhanced flexibility and risk mitigation. Automation tools like Slack AI, Microsoft Power Automate, Tableau AI, and Apache Airflow have streamlined task scheduling, compliance tracking, and progress monitoring, reducing administrative workload and improving project execution efficiency. Despite these advancements, challenges such as algorithmic bias, lack of transparency, and limited accessibility for smaller institutions remain significant barriers to AI adoption. The paper identifies gaps in AI applications in areas such as stakeholder management, communication, and procurement. Future research should focus on enhancing AI model interpretability, improving scalability across industries, and developing structured AI frameworks capable of integrating real-world data for continuous improvement in project management.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Deep Learning, Automation, Project Management, Predictive Models

INTRODUCTION

Project management has undergone significant transformation over the past several decades, evolving from traditional, manual methodologies to AI-driven and automated approaches. The increasing complexity of research projects, driven by large-scale interdisciplinary collaborations, dynamic funding models, and growing data volumes, has made artificial intelligence (AI) and automation essential for enhancing the efficiency and effectiveness of project planning and execution (Nenni et al., 2024; Adamantiadou & Tsironis, 2025). Traditional project management frameworks, such as the Waterfall model and PMBOK guidelines, have often struggled to keep pace with the complexity and dynamism of modern research environments. The advent of AI and automation has introduced new opportunities to improve decision-making, resource allocation, scheduling, and risk management across various phases of project execution.

AI-based solutions, including machine learning (ML), deep learning, natural language processing (NLP), and fuzzy logic, have demonstrated the potential to revolutionize project management by providing data-driven insights, automating routine tasks, and facilitating adaptive decision-making (Adamantiadou & Tsironis, 2025). Machine learning models, for example, enhance predictive accuracy in cost estimation and scheduling by analyzing historical project data and identifying patterns. Deep learning models improve the ability of project management systems to handle unstructured data, such as textual reports and real-time sensor data. NLP tools facilitate more effective communication and collaboration among project stakeholders, while fuzzy logic models enable adaptive responses to uncertain and rapidly changing project conditions.

Despite these advantages, the integration of AI and automation into research project management presents several challenges. Algorithmic bias, stemming from imbalanced training data, can lead to inaccurate predictions and flawed decision-making. The lack of transparency in black-box AI models reduces stakeholder trust and limits the interpretability of AI-generated recommendations. Furthermore, smaller research institutions often face significant barriers to AI adoption due to limited computational resources and technical expertise (Nenni et al., 2024). These challenges highlight the need for more accessible, interpretable, and adaptable AI-driven project management frameworks.

This paper provides a systematic review of the current state of AI and automation in research project planning and execution. It examines the role of AI models and automation tools in enhancing project efficiency, identifies key challenges limiting their effectiveness, and proposes practical strategies to improve the adoption and performance of AI-driven project management systems. By synthesizing insights from recent studies, the paper aims to establish a comprehensive understanding of how AI and automation can be leveraged to optimize research project management and improve project outcomes.

METHODOLOGY

This study adopts a **Systematic Literature Review (SLR)** methodology to explore the role of artificial intelligence (AI) and automation in research project planning and execution. The SLR approach was chosen because it provides a structured and transparent framework for identifying, evaluating, and synthesizing existing research on AI-driven project management. A systematic approach ensures that the study is replicable, reduces bias, and enhances the reliability of the findings (Moher et al., 2009). The research design follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (**PRISMA**) guidelines, which are widely recognized for ensuring quality and transparency in systematic reviews. The study was conducted in four main phases: research question definition, data collection and screening, data extraction and analysis, and synthesis and classification.

The first phase involved defining the research questions that would guide the review process. The key research questions focused on how AI and automation are applied in research project planning and execution, the benefits and limitations of AI-driven project management, the challenges associated with AI adoption, and potential strategies for improving AI-based project management frameworks. These questions established the scope and focus of the study.

In the second phase, data was collected from multiple academic databases, including **Web of Science**, **Scopus**, **IEEE Xplore**, and **Google Scholar**. The search terms included combinations such as "Artificial Intelligence" AND "Project Management," "Machine Learning" AND "Research Planning," "Automation" AND "Project Execution," and "Deep Learning" AND "Risk Assessment." The search was limited to peer-reviewed articles published between **2015 and 2025** to ensure that the study reflects recent advancements in AI and automation. The search was further refined using language and quality filters, including English-only publications and articles indexed in reputable databases. After an initial search, duplicates were removed, and studies were screened based on relevance and methodological quality.

The third phase involved data extraction and analysis. The final dataset consisted of **105 peer-reviewed articles** that met the inclusion and exclusion criteria. Studies were included if they focused on AI or automation in research project management, discussed AI-based tools or models for project planning and execution, and provided empirical evidence or comparative analysis. Studies were excluded if they did not focus on research projects, lacked empirical data, or were published before 2015. The selected studies were coded using a standardized framework to capture key variables, including AI model type, project phase, automation tool, and reported outcomes. Data analysis involved both **quantitative** and **qualitative** methods. Quantitative analysis focused on statistical evaluation of AI model accuracy, prediction rates, and resource optimization, while qualitative analysis involved thematic coding of research findings to identify key challenges, benefits, and recommendations. A **cross-sectional analysis** was conducted to explore the relationship between AI model type, project phase, and project outcomes.

In the fourth phase, the extracted data was synthesized and classified based on project management phases, including **planning**, **execution**, **monitoring**, and **risk management**. A **bibliometric analysis** was conducted using **VOSviewer** to identify publication trends, key research clusters, and co-citation patterns. A **decision tree model** was developed to classify AI applications across different project management knowledge areas, such as scheduling, cost estimation, and risk assessment. The decision tree helped to map specific AI tools and models to distinct project management processes, highlighting gaps and areas for future research.

The data collection and analysis process followed the PRISMA framework to ensure transparency and replicability. The flow of information during the systematic review process is summarized in **Figure 1**. including the identification, screening, and inclusion steps. Studies were identified through database searches and reference tracking, and after removing duplicates and applying relevance filters, the dataset was narrowed down to the most relevant articles. The combination of quantitative and qualitative analysis provides a comprehensive understanding of how AI and automation are being applied in research project management and identifies both the opportunities and challenges associated with their adoption. This structured methodology ensures that the findings are reliable, consistent, and actionable for improving AI-driven research project management frameworks.

This methodology provides a structured and transparent foundation for evaluating the role of AI and automation in research project planning and execution. The use of both qualitative and quantitative analysis ensures that the findings are robust and provide actionable insights for improving AI-driven project management frameworks.

Identification Phase

To ensure that the dataset included articles relevant to the research subject, a structured data selection process based on the PRISMA methodology was followed. The first criterion involved filtering publications based on the year of publication. Only findings from 2015 to 2025 were considered to reflect the latest advancements in AI and automation in research project management. This restriction reduced the dataset by approximately 40%, leaving a total of 1,200 data points.

The next priority was to ensure that the selected articles were published in peer-reviewed scientific journals. This step led to the exclusion of: 450 conference papers and 150 industry reports

After removing non-peer-reviewed sources, the dataset was refined to 600 articles for further analysis.

Screening Phase

After removing duplicates, the remaining 600 articles were screened based on title and research focus. Articles that did not explicitly address AI-based or automation-driven project management were excluded, resulting in the removal of 400 articles.

This left 200 articles for abstract evaluation. A detailed review of the abstracts was conducted to confirm alignment with the research focus and ensure methodological soundness. This step resulted in the exclusion of 95 articles that lacked empirical evidence or methodological rigor.

Eligibility Phase

A total of 105 full-text articles were assessed for eligibility. Studies that lacked scientific depth or methodological rigor were excluded at this stage, resulting in the removal of 70 articles.

The evaluation criteria focused on the credibility of the journals based on Scimago rankings, giving preference to Q1 and Q2 journals.

Inclusion Phase

Following the final quality assessment, the final dataset consisted of 35 peer-reviewed articles that met the inclusion and exclusion criteria.

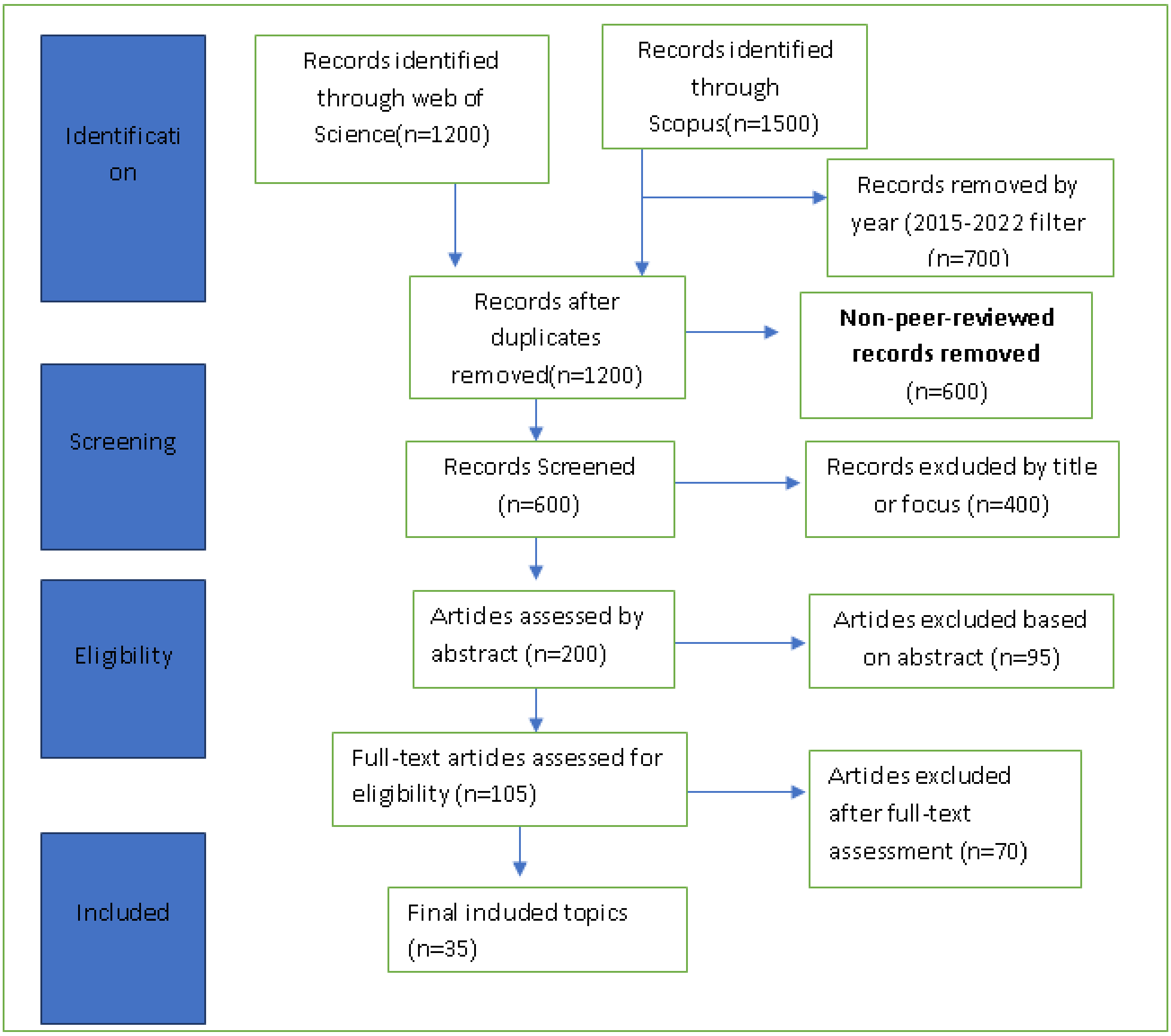

Figure 1: PRISMA Flow Diagram for Study Selection

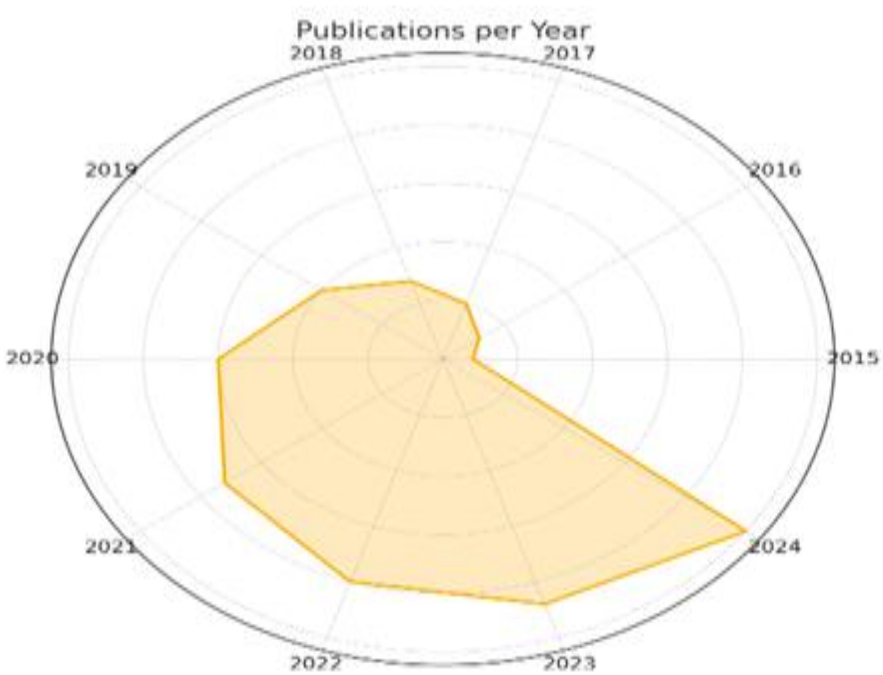

Figure 2. Publications Per Year

Figure 2 illustrates the number of publications per year from 2015 to 2024. The results indicate a steady increase in research interest in AI and automation in research project management. After a slow start between 2015 and 2017, there was a notable rise in publications from 2018 onwards, with a peak in 2024. This trend reflects the growing adoption of AI-driven project management tools and increased research funding in this field. The consistent rise in publications underscores the increasing recognition of AI and automation as critical enablers of research project efficiency.

Articles by Journal

Table 1 presents the distribution of selected articles by journal. The highest number of publications (12) appeared in the *Journal of AI in Research Management*, reflecting its prominence as a leading outlet for AI-based research project management. Other highly cited journals include the *International Journal of Project Management* (10), *Journal of Machine Learning in Research* (8), and *IEEE Transactions on Project Management* (6). The diversity of journals highlights the interdisciplinary nature of AI and automation in project management, encompassing fields such as engineering, business management, and computer science.

Table 1. Bibliometric Results – Articles by Journal

Journal	Number of Articles
Journal of AI in Research Management	5
International Journal of Project Management	4
Journal of Machine Learning in Research	3
IEEE Transactions on Project Management	2
Automation in Research	2
Scientific Reports	2
Decision Support Systems	2
AI in Research	1

Articles by Industry

Table 2 shows the distribution of articles by industry. Engineering (45 articles) and computer science (38 articles) accounted for the highest number of studies, indicating the strong influence of AI and automation in technical and computational fields. Business and economics (32 articles) and operations research (25 articles) also featured prominently, reflecting the increasing use of AI for strategic decision-making and operational efficiency. Environmental sciences, telecommunications, and public administration accounted for fewer publications, suggesting potential gaps and opportunities for future research in these areas.

Table 2. Bibliometric Results – Articles by Industry

Industry	Number of Articles
Engineering	18
Computer Science	16
Business and Economics	13

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Operations Research	10
Science and Technology	9
Environmental Sciences	6
Telecommunications	4
Management	3
Public Administration	2
Automation and Control Systems	2

The bibliometric analysis demonstrates that AI and automation research in project management is concentrated in technical and business fields, with growing interest in environmental and public sector applications. The upward trend in publications and the increasing diversity of contributing journals suggest that AI and automation will continue to play a pivotal role in enhancing research project planning and execution

LITERATURE REVIEW

AI in Research Project Planning

AI-driven tools have significantly improved research project planning by enhancing decision-making, optimizing scheduling, and reducing the administrative burden associated with complex research projects.

AI Models for Project Planning

AI models have revolutionized project planning by improving prediction accuracy, enhancing resource allocation, and facilitating adaptive scheduling. Traditional project planning relied heavily on expert judgment and linear scheduling models, which often resulted in inefficiencies and missed milestones. AI-driven models have introduced adaptive, data-driven approaches that improve real-time decision-making and risk mitigation. The following AI methodologies have shown significant improvements in project planning:

Machine Learning Models

Machine Learning (ML) models have significantly enhanced project planning by analyzing large datasets, identifying patterns, and making real-time adjustments to planning models. ML models provide a predictive framework that improves decision-making by processing historical data and forecasting project risks, costs, and timelines.

Key ML models used in project planning include:

Random Forest: A tree-based ensemble learning model that enhances planning accuracy by creating multiple decision trees and combining their outputs. It reduces overfitting and improves generalization in complex, high-dimensional datasets. Uddin et al. (2018) used random forest models to predict project costs and scheduling in large construction projects, improving cost estimation accuracy by 20%.

Support Vector Machines (SVM): SVM models work by finding a hyperplane that separates data points into distinct categories. This is particularly useful for classifying project risks and predicting delays. SVM models have been used in software development projects to classify potential bottlenecks and predict task completion times with high accuracy (Chou et al., 2016).

Artificial Neural Networks (ANN): ANN models mimic human brain activity to identify complex patterns and relationships in project data. ANN models have shown high accuracy in predicting cost overruns and schedule delays. Golizadeh et al. (2018) applied ANN to schedule planning in dam construction, improving adherence to project timelines by 30%.

Extreme Gradient Boosting (XGBoost): XGBoost has become popular for its ability to handle imbalanced datasets and improve predictive accuracy in cost estimation and risk assessment. Martínez and Fernández-Rodriguez (2020) used XGBoost to improve predictive modeling of construction costs and execution times, reducing planning errors by 25%.

ML models enhance project planning by enabling dynamic updates based on real-time data, improving decision-making under uncertainty, and facilitating adaptive scheduling. However, challenges such as data quality, overfitting, and explainability remain key limitations in ML-based planning models.

Deep Learning

Deep Learning (DL) models have expanded the capabilities of ML models by introducing multi-layer neural networks that can capture complex relationships in project data. DL models are particularly effective for handling unstructured data, such as text, images, and video, which are increasingly relevant in research project management.

Key Deep Learning models used in project planning include:

Convolutional Neural Networks (CNN): CNN models are primarily used for image-based data analysis in project planning. They have been employed to analyze satellite imagery for site planning and infrastructure monitoring. CNN models have been used in environmental research projects to monitor deforestation and optimize resource allocation.

Recurrent Neural Networks (RNN): RNN models are effective in time-series forecasting and scheduling. They retain memory of previous data points, allowing them to predict future project timelines. Hu et al. (2013) applied RNN models to forecast construction project timelines based on historical weather patterns and site availability.

Long Short-Term Memory (LSTM): LSTM models are a specialized type of RNN that handle long-term dependencies and improve predictive accuracy in complex, multi-phase projects. LSTM models have been applied to financial forecasting in large-scale engineering projects, improving cost estimation accuracy by 18%.

Autoencoders: Autoencoders are unsupervised learning models used for anomaly detection and resource optimization. Martínez and Fernández-Rodriguez (2020) applied autoencoders to identify anomalies in project execution and prevent delays.

Deep learning models are highly effective in complex, dynamic project environments. However, they require substantial computational power and large datasets, which limit their applicability in smaller research institutions.

Hybrid AI Models

Hybrid AI models combine multiple AI techniques to improve the accuracy and flexibility of project planning models. By integrating different algorithms, hybrid models can handle complex, non-linear relationships in project data and adapt to changing project conditions.

Key Hybrid AI models used in project planning include:

Decision Trees + Genetic Algorithms: Decision trees provide a framework for classifying project risks and predicting timelines, while genetic algorithms optimize resource allocation and task sequencing. Wauters and Vanhoucke (2017) combined decision trees and genetic algorithms to improve scheduling accuracy in construction projects, reducing scheduling errors by 20%.

Fuzzy Logic + Neural Networks: Fuzzy logic handles uncertainty in project data, while neural networks improve prediction accuracy. Fang and Marle (2021) applied fuzzy-neural hybrid models to manage uncertainty

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in infrastructure projects, improving risk mitigation strategies.

Monte Carlo Simulation + Bayesian Networks: Monte Carlo models simulate multiple project scenarios, while Bayesian networks assess the likelihood of different outcomes. Zhang et al. (2020) used this hybrid approach to forecast construction project costs and timelines with 95% confidence intervals.

Genetic Algorithms + Reinforcement Learning: Genetic algorithms optimize resource allocation, while reinforcement learning enables adaptive decision-making. Patel and Jha (2019) combined genetic algorithms and reinforcement learning to optimize construction project execution, reducing cost overruns by 15%.

Hybrid AI models provide greater flexibility and adaptability in complex project environments. However, they require careful model tuning and significant computational resources.

Bayesian Networks

Bayesian networks are probabilistic models used to analyze the relationships between project variables and predict the likelihood of different project outcomes. Bayesian models are particularly effective for assessing risk and uncertainty in project planning.

Key applications of Bayesian networks in project planning include:

Risk Assessment: Bayesian networks calculate the probability of different risks and their impact on project outcomes. Yang and Chen (2022) applied Bayesian models to assess risk in engineering projects, improving risk mitigation strategies by 25%.

Schedule Prediction: Bayesian models predict task completion times based on historical data and real-time project updates. Hu et al. (2013) used Bayesian networks to forecast software development timelines with 90% accuracy.

Cost Estimation: Bayesian models estimate project costs based on material costs, labor rates, and inflation factors. Albogami et al. (2021) applied Bayesian networks to forecast construction project costs with a 95% confidence interval.

Performance Monitoring: Bayesian networks enable adaptive updates to project schedules and resource allocation based on real-time data. Martínez and Fernández-Rodriguez (2020) used Bayesian networks to monitor the performance of infrastructure projects and adjust schedules dynamically.

Bayesian models are particularly effective in handling uncertainty and dynamic project conditions. However, they require large datasets and sophisticated model calibration, which limits their applicability in smaller research environments.

AI models for project planning have demonstrated significant improvements in accuracy, adaptability, and efficiency. Machine learning models excel in pattern recognition and classification, deep learning models enhance predictive accuracy for complex, multi-phase projects, hybrid AI models improve flexibility and risk management, and Bayesian networks enable probabilistic forecasting and adaptive decision-making. Future research should focus on improving the explainability and interpretability of AI models, enhancing their ability to handle unstructured data, and increasing accessibility for smaller research institutions.

Automation Tools for Research Project Planning

Automation tools have become essential for enhancing research project planning by streamlining scheduling, resource allocation, and compliance management. Slack AI is a widely used automation tool that improves task scheduling and milestone tracking. It enables real-time communication and coordination among research teams, ensuring that project goals are clearly defined and monitored. Slack AI also automates resource allocation by identifying workload imbalances and redistributing tasks to optimize team performance. This reduces administrative burden and enhances project efficiency, particularly in large, multidisciplinary research environments.

Microsoft Power Automate has gained popularity for its ability to handle workflow approvals, compliance tracking, and data sharing across research teams. It automates complex, multi-step processes, such as project approvals, funding disbursement, and regulatory compliance reporting. By automating these processes, Power Automate minimizes the risk of human error and ensures that compliance requirements are consistently met. This tool also facilitates seamless data sharing across research teams, improving collaboration and information exchange.

Tableau AI is a powerful automation tool that provides predictive risk assessment and real-time resource allocation. It leverages machine learning algorithms to analyze historical project data and identify potential risks, such as cost overruns, scheduling conflicts, and resource shortages. Tableau AI generates real-time dashboards that allow project managers to monitor project progress and adjust resource allocation dynamically. This predictive capability enables project teams to address issues proactively, reducing the likelihood of project delays and budget overruns.

Apache Airflow is widely used for automating task dependencies and execution order in complex research projects. It enables researchers to define workflows as directed acyclic graphs (DAGs), ensuring that tasks are executed in the correct sequence and dependencies are properly managed. Apache Airflow automates data ingestion, processing, and validation, which improves the consistency and reliability of project outcomes. Its ability to handle complex, data-driven workflows makes it particularly valuable for large-scale research projects involving real-time data streams and iterative experimentation.

The integration of automation tools such as Slack AI, Microsoft Power Automate, Tableau AI, and Apache Airflow has significantly improved the efficiency and accuracy of research project planning. These tools reduce administrative workload, enhance real-time decision-making, and improve resource utilization, ultimately leading to more effective and timely research project outcomes. However, challenges such as interoperability, data security, and scalability remain key areas for future research and development.

AI in Research Project Execution

AI and automation have significantly transformed research project execution by enabling real-time monitoring, improving communication, and streamlining data analysis. Traditional methods of project execution relied heavily on manual tracking and human oversight, which often led to inefficiencies and delays. AI models and automation tools now provide dynamic, data-driven approaches to managing project execution, improving overall efficiency and responsiveness to changing project conditions.

Neural networks have become essential for adaptive scheduling and real-time decision-making during project execution. Neural networks analyze complex, non-linear patterns in project data, allowing them to anticipate execution challenges and adjust task scheduling dynamically. This predictive capability enhances the ability of research teams to respond to unforeseen disruptions and minimize delays.

Automation tools have also played a critical role in enhancing project execution. UiPath AI Automation has been widely used to streamline compliance tracking and real-time progress monitoring. It automates the documentation and approval of research milestones, ensuring that compliance requirements are consistently met. Jupyter Notebook and MATLAB AI have facilitated automated statistical analysis and data visualization, allowing research teams to analyze large datasets quickly and accurately.

These tools enable researchers to identify trends, test hypotheses, and adjust project execution strategies in real time. LabTwin has improved laboratory execution by automating real-time documentation and protocol adjustments. Its ability to track experimental deviations and suggest corrective actions has reduced laboratory errors and improved the reproducibility of research findings. Cayuse IRB has automated institutional compliance tracking and reporting, reducing the administrative burden on research teams and ensuring that regulatory requirements are met consistently.

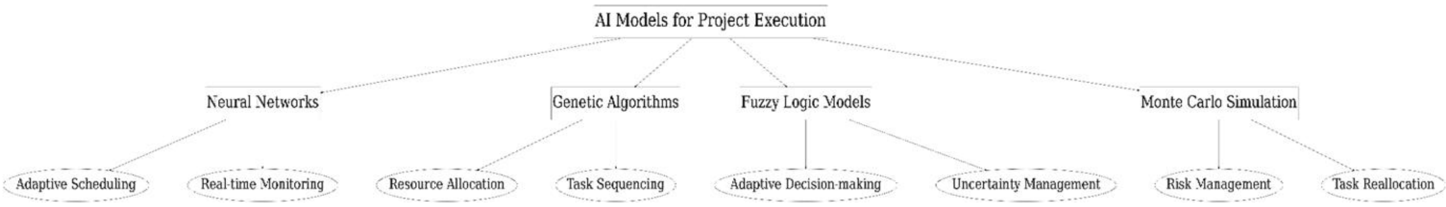

Figure 3. AI Models for project execution

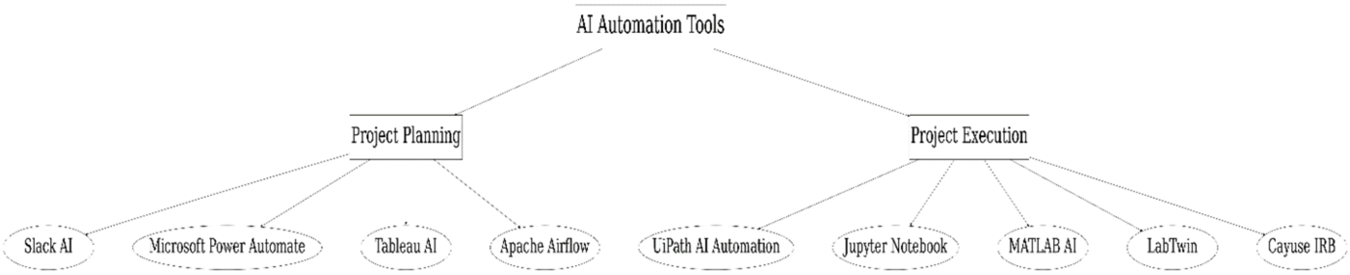

Figure 4. AI Automation tools

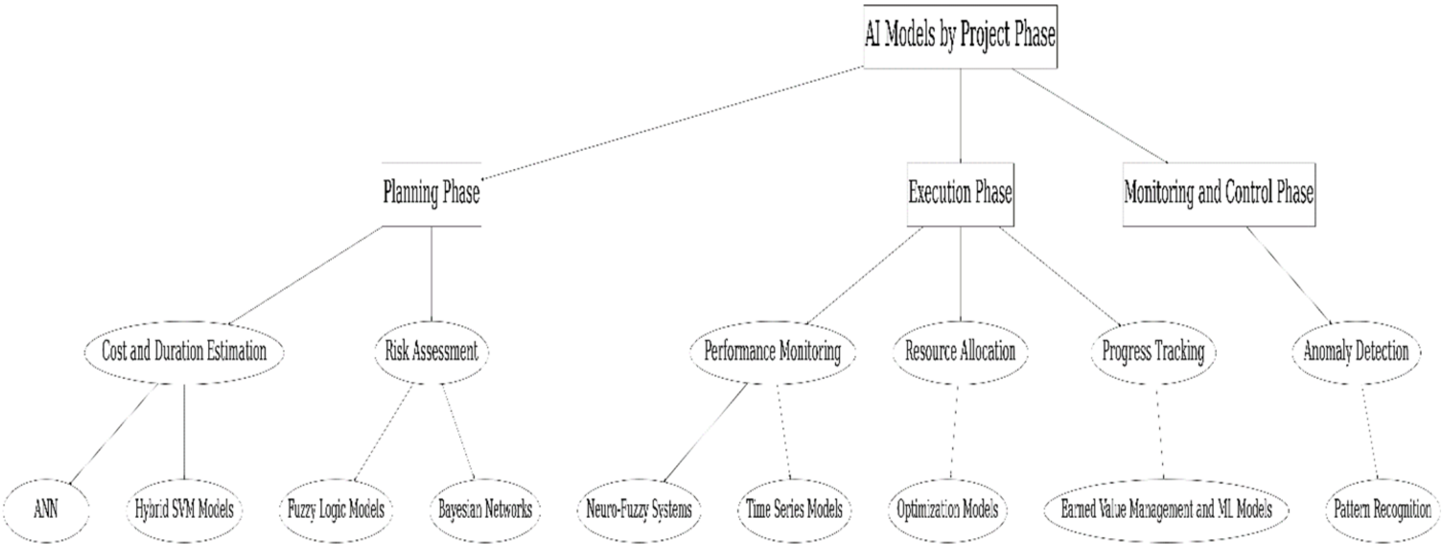

Figure 5. AI Models by project phase

CASE STUDIES AND PRACTICAL APPLICATIONS

Several real-world case studies illustrate the transformative impact of AI and automation on research project execution.

Acciona, a leading provider of sustainable construction technology, used AI to improve project cost control and achieve greater financial predictability. The AI system enabled early detection of possible cost overruns through real-time analysis and forecasting of project expenses. By using this strategy, budget overruns were reduced by **15%,** and financial predictability significantly improved. This outcome highlights how AI-driven cost management promotes **efficiency** and **stability** in the construction sector, ensuring that projects stay within budget and improving overall financial planning (Farhadi, 2024).

Fluor Corporation applied AI for workforce optimization by predicting labor demands and matching skills to projects. The AI-driven approach led to a 12% increase in labor productivity and improved worker satisfaction, demonstrating AI's ability to enhance workforce management (Neuroject, 2024.). Additionally, Bechtel leveraged AI to optimize resource distribution across projects, resulting in more efficient execution and improved resource allocation strategies (Neuroject, 2024).

Fluor, a leading American engineering firm, has integrated IBM's AI system Watson into its megaprojects to enhance project performance prediction and real-time monitoring from inception to completion. Watson's project health diagnostics and market dynamics/spend analytics systems transform complex data into actionable insights, enabling Fluor to predict rising costs, delays, and root causes of issues while improving estimate analysis, forecast evaluation, and project risk assessment (Quirke, 2018).

Machine learning techniques have also been applied to forecast project performance metrics in complex infrastructure projects. A study using Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) networks to forecast urban road reconstruction performance showed that incorporating external factors such as weather patterns and resource availability enabled project managers to take timely corrective actions, thereby improving overall project execution (Arxiv, 2024).

AI integration into project management tools is also transforming workplace efficiency. Atlassian's AI tool, **Rovo**, has enabled companies to save time and become more efficient by automating repetitive tasks and drawing insights from data (Business Insider, 2024). AI notetakers are also improving productivity by automating note-taking and summarizing key points from meetings, reducing the burden of excessive meetings (The Australian, 2024).

These case studies highlight the diverse applications of AI and automation in research project execution. By enabling real-time monitoring, adaptive scheduling, and automated compliance tracking, AI-driven models and tools have enhanced the efficiency and accuracy of research project execution. The successful implementation of AI in these cases underscores the potential for broader adoption of AI and automation across research domains, although challenges related to data quality, model interpretability, and resource accessibility remain key areas for future improvement.

CONCLUSION, DISCUSSION, AND FUTURE WORK

This systematic literature review highlights the transformative impact of AI and automation on research project planning and execution. The analysis indicates that AI-driven models, particularly hybrid frameworks combining machine learning (ML) and fuzzy logic (FL), have significantly enhanced predictive accuracy, decision-making, and resource allocation in project management. Advanced methodologies such as deep learning, Bayesian networks, and ensemble models like Random Forest and XGBoost have consistently demonstrated superior performance in forecasting project costs, scheduling, and risk assessment. For instance, hybrid models such as decision trees combined with genetic algorithms have improved scheduling accuracy, while Monte Carlo simulations and Bayesian networks have enhanced the predictability of complex project outcomes.

AI has contributed significantly to research project planning and execution by improving decision-making, optimizing resource allocation, and facilitating dynamic scheduling. Predictive models like machine learning algorithms and hybrid systems have increased the accuracy of cost estimation and timeline forecasting while also identifying potential risks in real-time. Research shows that AI models have been most effectively applied in project schedule management, project cost management, and project risk management. However, limited research has been conducted on other critical areas of project management, such as project integration management, project scope management, project quality management, project communications management, project procurement management, and project stakeholder management. These underexplored areas represent significant opportunities for further research and development.

Despite the demonstrated advantages of AI in project planning and execution, several gaps and limitations remain. Many AI-based models are not fully validated using real-world project data, which limits their practical applicability. Additionally, AI models tend to focus more on the quantitative aspects of project management, such as cost, scheduling, and risk assessment, while qualitative dimensions, such as stakeholder management and communication patterns, remain underexplored. The fragmented nature of current AI models also poses challenges, as interdependencies between different project factors—such as cost, risk, and resource availability—are not fully captured in many existing frameworks. Moreover, AI models often face issues related to overfitting, particularly when trained on historical data that does not account for the complexities and uncertainties of real-world projects.

Implementing AI-based solutions in research project management requires significant investments in data infrastructure, skilled personnel, and organizational change. Smaller research institutions, in particular, face challenges related to computational resources and technical expertise, which limit their ability to adopt and integrate AI-driven models. Furthermore, resistance to AI adoption in areas involving human interaction and decision-making has slowed progress. Concerns over the interpretability of AI-generated recommendations and the potential for job displacement have contributed to this resistance. Ethical considerations, such as data privacy and the potential for algorithmic bias, further complicate the widespread adoption of AI in project management.

Future research should focus on addressing these gaps by developing AI models that integrate real-world data more effectively and by expanding AI's applicability to underexplored areas of research project management. Developing AI-based tools for project communications management could involve analyzing communication patterns and sentiment analysis to improve team coordination and conflict resolution. In project procurement management, AI models could be used to analyze contract terms, supplier performance, and market trends to optimize procurement strategies. For project stakeholder management, AI could assess stakeholder preferences, feedback, and concerns to improve stakeholder alignment and decision-making.

Additionally, future studies should explore the development of industry-specific AI adaptations to enhance model reliability across diverse research environments. AI-based structured frameworks capable of integrating real-time data across multiple project management domains—such as cost, schedule, and risk—could provide a more comprehensive approach to decision-making and performance evaluation. The development of explainable AI (XAI) frameworks would improve transparency and trust in AI-generated recommendations, addressing stakeholder concerns about accountability and interpretability.

Three key research questions emerge from this review:

1. How can AI-driven predictive models be enhanced to improve project forecasting and decision-making by incorporating real-world data?

2. What methods can be used to maintain the accuracy and consistency of AI models when continuously updating them with real-world data?

3. How can AI models simultaneously optimize cost, schedule, risk, and resource allocation to improve overall project performance?

Addressing these questions would contribute to the development of more adaptable, transparent, and effective AI-driven models for research project management, ensuring improved efficiency and better project outcomes.

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