Journal of Project Management 11 (2026) 247–272

Contents lists available at GrowingScience

Journal of Project Management

homepage: www.GrowingScience.com/jpm

Project portfolio management in the age of artificial intelligence: A review of challenges, key features, and future research directions

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C H R O N I C L E

Article history:
Received June 10, 2025
Received in revised format September 3, 2025
Accepted September 23 2025
Available online September 23 2025

Keywords:
Project portfolio management
Artificial intelligence
Machine learning
Deep learning
Neural network
Reinforcement learning

A B S T R A C T

The rapid advancement of artificial intelligence (AI) has revolutionized project portfolio management (PPM), as it has in many other areas, by introducing data-driven methods that improve decision-making, risk assessment, and strategic alignment. Unlike traditional project management, which emphasizes individual project execution, PPM requires balancing multiple initiatives to optimize value creation and resource allocation. This paper presents a systematic review of scientific research on the integration of AI techniques into PPM, focusing on their applications, benefits, and challenges. The review synthesizes findings from 73 peer-reviewed studies covering a wide range of AI methodologies, such as machine learning, deep learning, neural networks, reinforcement learning, natural language processing, and hybrid optimization models. These approaches have been applied in diverse fields, including information technology, construction, healthcare, defense, energy, and telecommunications. Analysis shows that AI significantly improves project portfolio performance by predicting project outcomes, identifying interdependencies, optimizing resource allocation, and supporting adaptive strategies in dynamic environments. In addition, advanced AI tools provide project portfolio managers with predictive and prescriptive analytics, transforming PPM from reactive monitoring to proactive governance. Despite these advances, challenges remain regarding data quality, organizational readiness, and interpretability of AI-based models. Concerns about transparency, ethical implications, and integration with existing management frameworks also hinder wider adoption. However, recent developments indicate a growing trend toward hybrid systems that combine AI with traditional decision-making models, increasing both accuracy and practical applicability. This review contributes to theory and practice by synthesizing current knowledge, highlighting research gaps, and identifying emerging directions such as the use of large language models, ensemble methods, and sustainability-focused project portfolio optimization. The findings highlight the transformative potential of AI in advancing PPM and provide valuable insights for researchers and practitioners seeking to design smarter, more adaptive, and more sustainable project portfolio management strategies.

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1. Introduction

Over the past two decades, AI has experienced unprecedented growth, evolving from theoretical research into a transformative technology with widespread real-world applications (Russell & Norvig, 2021). Advances in machine learning algorithms, the expansion of neural networks, the emergence of deep learning, and access to vast datasets have enabled AI systems to perform tasks that once required human intelligence. These include understanding natural language, recognizing images and speech, making complex decisions, and even generating creative content. As a result, AI has been integrated into a broad range of

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ISSN 2371-8374 (Online) - ISSN 2371-8366 (Print)
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doi: 10.5267/j.jpm.2025.9.006

industries (Nichols et al., 2019). In healthcare, it enhances diagnostic accuracy, supports medical imaging analysis, and accelerates drug development (Sharma et al., 2022). In finance, AI drives fraud detection, risk assessment, and personalized financial services (Li et al., 2023). The transportation sector benefits from AI in the development of self-driving cars and traffic management systems (Sadek, 2007). Moreover, in education, AI powers adaptive learning platforms that tailor content to individual student needs, while in manufacturing, it optimizes supply chains and predictive maintenance (Malik et al., 2019). The continuous evolution of AI suggests that its impact will only deepen, shaping not only the economy but also the way people interact with technology and the world around them.

One of these areas is PPM. A project portfolio is a strategic framework through which organizations manage a collection of projects, programs, and other related initiatives in a coordinated manner to achieve their overarching business objectives (Archer & Ghasemzadeh, 1999). Unlike individual project management, which focuses on delivering specific outputs within time and budget constraints, portfolio management adopts a macro-level perspective. It emphasizes selecting, prioritizing, and balancing projects based on factors such as strategic alignment, resource availability, expected value, risk level, and overall contribution to organizational goals (Blichfeldt & Eskerod, 2008). By evaluating projects collectively rather than in isolation, organizations can optimize resource utilization, avoid redundant efforts, and ensure that their limited investments are directed toward the most impactful initiatives (Martinsuo, 2013). Moreover, PPM provides a governance structure that allows senior leadership to continuously monitor performance, respond to changes in the external environment, and realign the portfolio as needed. In today's complex and dynamic business landscape, where agility and strategic foresight are critical, PPM serves as a crucial tool for enhancing organizational performance, enabling innovation, and maintaining competitive advantage (Levine, 2005).

AI has emerged as a transformative force in PPM, offering advanced tools and methodologies that enhance strategic planning, decision-making, and execution oversight. The integration of various AI subfields including machine learning, deep learning, artificial neural networks, reinforcement learning, expert systems, and natural language processing enables organizations to manage complex portfolios with greater precision and adaptability (Vergara et al., 2025). Machine learning models, for example, are used to evaluate project proposals by learning from historical performance data, thereby identifying patterns associated with successful outcomes or high-risk indicators. Deep learning, particularly through the use of convolutional and recurrent neural networks, can process high-dimensional data such as financial metrics or timeline fluctuations to forecast delays, cost overruns, or resource bottlenecks (Agrawal et al., 2025). Reinforcement learning, which mimics human decision-making through trial and error, supports real-time portfolio optimization by dynamically allocating resources or adjusting project priorities based on environmental feedback and shifting constraints (Soleymani et al., 2024). Furthermore, expert systems can encapsulate domain-specific knowledge to guide project selection aligned with strategic business goals, while NLP can automate the extraction and analysis of qualitative data from project reports, stakeholder communications, and documentation. AI-powered dashboards and decision support systems offer real-time visualization and recommendation engines that help portfolio managers adapt to changes and make evidence-based adjustments. The synergy of these AI technologies not only streamlines routine administrative tasks but also enables predictive and prescriptive analytics that were previously unattainable through traditional methods. As a result, AI facilitates a shift from reactive to proactive portfolio management, ensuring that project investments are optimized for value creation, risk mitigation, and long-term organizational sustainability (Tian et al., 2022).

Given the recent advances in artificial intelligence science in recent years, the integration of artificial intelligence into PPM has attracted considerable attention from researchers and practitioners, driven by the potential of artificial intelligence to increase efficiency, accuracy, and strategic decision-making at different stages of a project. In this paper, we conduct a rigorous and methodologically sound systematic review of scholarly studies that apply artificial intelligence techniques to the field of project management. The aim of our review is to examine how artificial intelligence can be used to support a wide range of project portfolio management functions, including project planning, risk assessment, resource allocation, performance monitoring, and stakeholder communication. By systematically identifying, evaluating, and synthesizing the relevant peer-reviewed literature, we seek to provide a comprehensive understanding of the current landscape of AI applications in project management. This includes a review of the types of AI methods used, such as machine learning algorithms, deep learning models, natural language processing tools, predictive analytics, and decision support systems, as well as the specific project management domains in which they are applied. Furthermore, this review highlights the benefits, limitations, and challenges ahead in adopting AI in project management, and provides important insights into practical implications and theoretical advances. Ultimately, this review aims not only to outline the latest advances in this interdisciplinary research area, but also to identify emerging trends, research gaps, and future opportunities that can guide further studies and inform practitioners seeking to implement AI-based solutions in project management environments.

Fig. 1 shows a word cloud that illustrates the intersection between the fields of AI and project portfolio management. This visualization highlights commonly used terms and concepts, thereby providing an overview of the dominant themes in the literature. To produce this figure, bibliographic data were retrieved from the Web of Science (WOS) database, ensuring comprehensive coverage of relevant scientific publications. The dataset was subsequently processed and analyzed using R software, which allowed the construction of a word cloud and the identification of key research trends and thematic clusters.

Fig 1. Intersection between the fields of AI and project portfolio management

As can be seen in Fig. 1, terms such as project portfolio selection, management, model, and selection demonstrate the central role of decision-making frameworks in project prioritization and allocation. From an AI perspective, keywords such as genetic algorithm, machine learning, artificial neural network, recurrent neural network, and data mining emphasize the application of computational and learning-based methods to optimize project portfolio decisions. Meanwhile, concepts such as optimization, algorithm, framework, and methodology reflect the technical strategies commonly used in integrating AI into project portfolio management. From a PPM perspective, words such as uncertainty, risk management, sustainability, success, performance, and decision making highlight the critical management concerns that AI techniques aim to address. Collectively, these terms illustrate how AI contributes to advanced analytical capabilities to improve project portfolio selection, enhance performance, and manage risks and uncertainties in complex project environments. Among the concepts used in this article are the following.

- **Project portfolio management (PPM):** PPM is the centralized process of selecting, prioritizing, and managing multiple projects to align with strategic goals. It ensures optimal resource use and maximizes value across the organization (Rad & Levin 2006).
- **Artificial intelligence (AI):** AI is the simulation of human intelligence processes by machines, especially computer systems. It enables systems to learn from data, make decisions, and perform tasks that typically require human intelligence (Ertel 2024).
- **Machine learning (ML):** ML is a subset of artificial intelligence that enables systems to automatically learn and improve from experience without being explicitly programmed. It focuses on developing algorithms that can identify patterns in data and make predictions or decisions (Mahesh 2020).
- **Neural network (NN):** A NN is a machine learning model inspired by the structure of the human brain, consisting of layers of interconnected nodes (neurons). It processes data by passing inputs through these layers to recognize patterns and make predictions or classifications (Dongare et al., 2012).
- **Recurrent neural networks (RNNs):** RNNs are a type of neural network designed to process sequential data by maintaining a memory of previous inputs through internal loops. They are commonly used in tasks like language modeling, speech recognition, and time series prediction (Grossberg, 2013).
- **Deep learning (DL):** DL is a subset of machine learning that uses multi-layered neural networks to model complex patterns in large amounts of data. It excels in tasks such as image recognition, natural language processing, and autonomous driving (Kim, 2016).
- **Reinforcement learning (RL):** RL is a type of machine learning where an agent learns to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. The goal is to learn a policy that maximizes cumulative rewards over time (Wiering & Van Otterlo, 2012).
- **Deep reinforcement learning (DRL):** DRL combines reinforcement learning with deep neural networks to enable agents to make complex decisions directly from high-dimensional inputs like images. It is used in advanced applications such as robotics, game playing, and autonomous systems (Arulkumaran et al., 2017).
- **Genetic algorithm (GA):** GAs are optimization techniques inspired by natural selection. They work by evolving a population of candidate solutions through selection, crossover, and mutation. Over successive generations, better solutions emerge based on their performance or fitness (Mitchell, 1998).

Given the rapid advancement and increasing importance of AI in contemporary management practices, it is essential for managers and decision-makers to remain aware of emerging trends and newly developed tools (Malik et al., 2019). Accordingly, the purpose of this research is to identify, collect, screen, and systematically analyze existing studies on AI-based tools, techniques, and methods applied in the field of project PPM. Beyond mapping the current body of knowledge, this study also seeks to synthesize findings and categorize them according to the recognized knowledge areas of PPM, such as portfolio governance, portfolio risk management, resource allocation, performance measurement, and strategic alignment. By doing so, the review aims to provide a structured understanding of how AI contributes to enhancing decision-making processes, improving portfolio outcomes, and addressing uncertainties in dynamic project environments. Ultimately, the study aspires to highlight not only the achievements of previous research but also the challenges, research gaps, and promising directions for future investigation.

- What types of AI tools, techniques, and methods have been applied in the domain of PPM?
- How have approaches such as machine learning, genetic algorithms, neural networks, and data mining been utilized in portfolio selection and prioritization?
- To what extent do hybrid approaches (e.g., AI combined with traditional decision-making models) appear in the literature?
- Which AI techniques are most frequently applied to deal with uncertainty and risk in PPM?
- What benefits have been reported regarding the integration of AI into PPM processes?
- How does AI improve decision-making, efficiency, and accuracy in portfolio selection and resource allocation?
- What technical, organizational, or cultural challenges hinder the adoption of AI in PPM?
- How do data quality, availability, and privacy issues affect the effectiveness of AI applications in PPM?
- What research gaps can be identified in the current body of knowledge at the intersection of AI and PPM?
- How can artificial intelligence tools be leveraged to enhance metaheuristic algorithms applied to single-objective and multi-objective optimization problems in project portfolio management?

The paper is systematically divided into six major sections to provide clarity and logical flow. The second section introduces the theoretical foundations and contextual background necessary for understanding the scope of the study. This part reviews relevant literature and sets the stage for the subsequent analysis. The third section outlines the research methodology in detail, including the process of selecting relevant studies, the databases and sources consulted, and the analytical framework employed to evaluate and synthesize the findings. Section 4 is dedicated to presenting the core results of the systematic review, highlighting the patterns, trends, and key outcomes identified across the examined literature. Section 5 moves beyond reporting findings to engage in a critical discussion. It explores the practical and theoretical implications of the results, draws attention to the limitations of existing studies, and identifies challenges that must be addressed. Additionally, this section suggests avenues for future research that can expand and refine the field. The final part of the paper, Section 6, concludes the study by synthesizing the most important insights, reiterating the contributions made, and explicitly addressing the research questions posed at the outset. This structured organization ensures that readers can follow the progression from background to methodology, findings, discussion, and conclusion in a coherent manner.

2. Background

In the context of increasingly complex and dynamic project environments, effective PPM has become critical for aligning strategic objectives with resource allocation and project execution. Traditional PPM approaches often struggle to manage high-dimensional data, uncertainty, and real-time decision-making needs. As a result, researchers and practitioners are exploring AI as a game-changer for improving portfolio-level decisions. AI technologies such as machine learning, deep learning, natural language processing, and optimization algorithms offer promising capabilities for predicting project performance, identifying risk patterns, automating prioritization, and adapting to evolving project landscapes (Vergara et al. 2025). Recent advances in AI have led to its integration into various layers of PPM, including project selection, resource optimization, risk management, and value realization. Unlike traditional rule-based methods, AI systems can learn from historical and contextual data to uncover hidden relationships and improve forecast accuracy. For example, AI-based predictive analytics can estimate the probability of project success, suggest optimal investment mixes, and adjust portfolio configurations based on variable constraints and business objectives. As organizations seek greater agility and flexibility, understanding how AI can contribute to smarter and more adaptive investment portfolio strategies is both timely and essential.

Recently, artificial intelligence has been used in various studies in project portfolio management, including (Tselios et al., 2013; Tian et al., 2022; Mo et al., 2020; Relich & Pawlewski, 2017; Faezy Razi & Hooman Shariat, 2017; Golghamat Raad et al., 2020; Tian et al., 2022; April et al., 2004; Micán et al., 2021. Jang, 2019; Chen, et al. 2024; Vergara et al., 2025; Zaidouni & Bellabdaoui, 2024; Araújo et al., 2023; Elnabwy et al., 2024), and etc. A complete list of these studies is given in Table 2 of the following section. A substantial body of literature exists on the application of AI in PPM, including the examples previously discussed. These studies have been systematically collected, analyzed, and categorized into relevant project management knowledge areas, and are presented in this paper. In addition, several recent review articles provide comprehensive overviews of prior research concerning the use of AI techniques to enhance project management practices or to offer insights into related challenges. A selection of these studies, along with their respective areas of focus, is summarized in Table 1.

Table 1
Review articles conducted in the field of PPM

Author/Year	Main topic	Type
Bahroun et al. (2023)	Artificial intelligence application in project scheduling: a systematic review, bibliometric analysis, and prospects for future research	Systematic, Bibliometric
Mohagheghi et al. (2019)	Project portfolio selection problems: a review of models, uncertainty approaches, solution techniques, and case studies	Systematic
Ha & Madanian (2018)	The Potential of Artificial Intelligence in IT Project Portfolio Selection	Descriptive
Marchinares and Aguilar-Alonso (2020)	Project Portfolio Management Studies Based on Machine Learning and Critical Success Factors	Classification
Micán et al. (2021)	Project portfolio risk management: a structured literature review with future directions for research	Structured
Vergara et al. (2025)	Trends and Applications of Artificial Intelligence in Project Management	Bibliometric

In the following, we will examine these six studies and explain their differences with our work. The paper by (Ha & Madanian n.d.) examines the complexity of IT projects and emphasizes the need for cross-team coordination and strategic alignment in project portfolio selection. It reviews current challenges and tools, noting the limitations of existing methods in handling uncertainty, risk, and dynamic environments. The authors highlight the potential of AI applications and propose future research directions to enhance decision-making and portfolio optimization in the IT industry. PPM plays a vital role in organizational growth by aligning resources, planning projects, and achieving strategic objectives. With the increasing volume of project-related data, there is a growing need for models that can efficiently process and interpret this information. The study by Marchinares & Aguilar-Alonso (2020) reviews the application of ML in PPM, identifying methods and success factors that enhance project planning and execution. From 122 studies reviewed, 21 were analyzed in detail, yielding seven ML methods and 18 critical success factors for improving PPM practices.

Micán et al. (2021) present a structured review of project portfolio risk management (PPRM) literature, analyzing 62 international journals. The review identifies four key themes: (1) the influence of risk management on project portfolio success, (2) interdependencies among risks and projects, (3) identification of project portfolio risks, and (4) methods for PPR assessment. The findings highlight PPRM's theoretical foundations in project portfolio theory and decision-making, with practical approaches focused on risk sources and assessment techniques. The study concludes by outlining four research directions, emphasizing the integration of PPRM into enterprise risk management, its strategic impact, advanced assessment mechanisms, and its treatment as a complex dynamic system. The integration of AI is reshaping project management by enhancing planning, execution, and monitoring. Vergara et al. (2025) conduct a bibliometric analysis of AI applications in project management over the past decade, identifying key themes such as machine learning, decision-making, resource optimization, and generative AI. The findings show that China, India, and the United States are leading in publication volume, while the United Kingdom and Australia achieve the highest citation impact. The study also outlines opportunities, challenges, and future research directions for advancing AI-based project management.

Mohagheghi et al. (2019) offer a comprehensive review of project portfolio selection and optimization, analyzing over 140 studies from the last twenty years. The review examines evaluation criteria, solution approaches, uncertainty modeling, and practical applications, highlighting a shift toward incorporating social and environmental factors alongside financial considerations. While metaheuristic and heuristic methods dominate solution techniques, areas such as artificial intelligence, expert systems, and big data remain underexplored. The authors suggest future research directions including integrating sustainability, resilience, external investment factors, and leveraging AI with big data and fuzzy stochastic optimization methods. Bahroun et al. (2023) analyze the application of ML techniques to project scheduling problems (PSPs) through a bibliometric and systematic review of 104 papers published from 1985 to 2021. Key ML methods identified include artificial neural networks, Bayesian networks, and reinforcement learning, often integrated with classical metaheuristics. The majority of studies focus on resource-constrained PSPs, with few addressing project portfolio management. The review highlights the emerging role of AI in PSPs and outlines research gaps and future directions.

A search using the WOS database identified six relevant review articles that are to varying degrees relevant to the topic under review. However, upon closer inspection, it becomes clear that none of these existing studies provide a comprehensive or systematic review that specifically focuses on the applications of AI to the project portfolio problem. While some articles address related topics or broader applications of AI in project management, there is no dedicated, in-depth review of how AI techniques are used to address the unique challenges of project portfolio management in the literature. Among the criteria that we examine in this paper that have not been addressed in previous studies are the application and combination of AI methods in single and multi-objective portfolio optimization problems, the classification of master cases, the objectives of using tools such as clustering, and the hand-holding of AI tools used in the studies. This significant gap highlights the need for a comprehensive review. Consequently, the present study aims to fill this gap by providing a rigorous and structured analysis of existing research on the intersection of AI and project portfolio management. Our goal is to consolidate current knowledge, identify emerging trends, and highlight areas that require further investigation, thereby contributing to academic understanding and practical advances in this field.

3. Methodology

The methodology adopted in this review involves several systematic steps. First, relevant studies were collected from reputable scientific databases to ensure comprehensive coverage of the existing literature. In the next step, review criteria were defined based on the objectives and scope of the research, providing a structured framework for analysis. Subsequently, the collected studies were reviewed in detail based on the specified criteria, allowing for an in-depth assessment of their approaches and findings. After this step, the studies were categorized and organized based on the specified criteria to identify patterns, similarities, and differences in the literature. Finally, the main challenges in the reviewed works were highlighted and potential directions for future research were suggested. This structured methodology ensures transparency and rigor in the review process and is based on the study of Sundaram & Berleant (2023). The overall framework of this methodology is shown in Fig. 2.

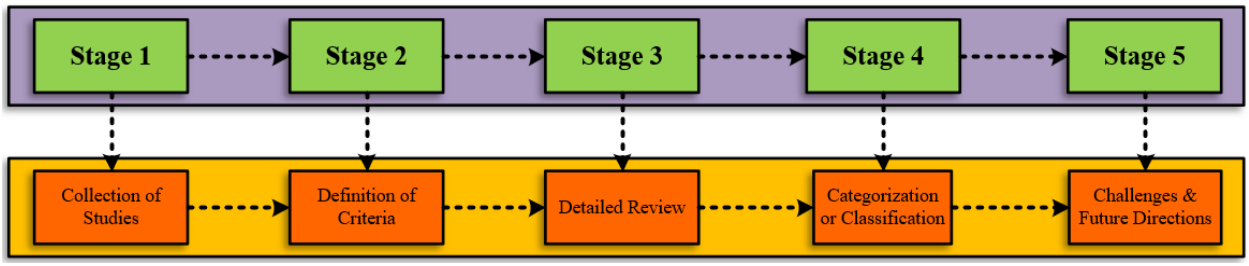

Fig. 2. Methodology Structure

To begin the text retrieval process, carefully selected search terms, as outlined in the following section, were entered into the WOS search engine. These terms were designed to provide results that were directly relevant to the main research questions and to ensure a focused and thorough exploration of the topic. Fig. 3 graphically illustrates the query searched in the database.

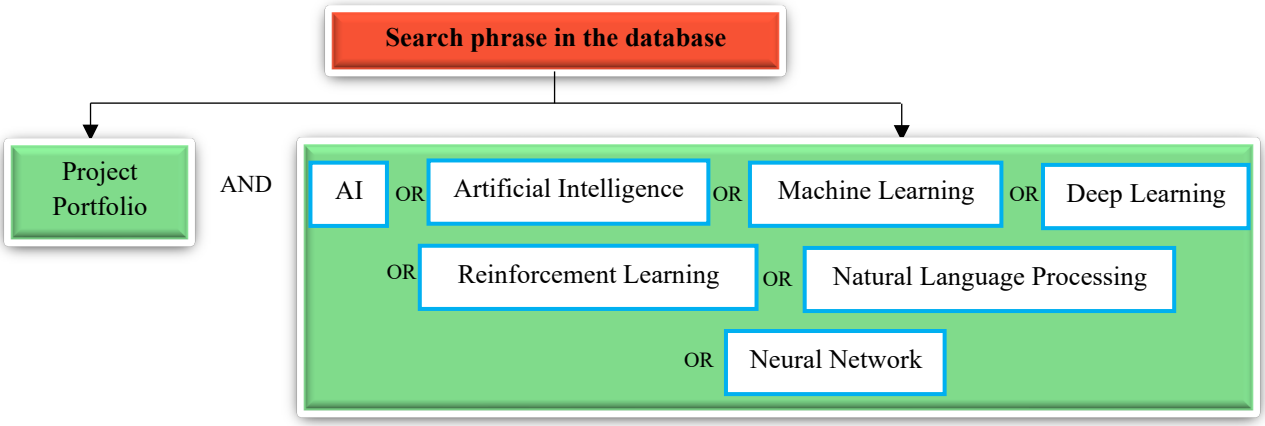

Fig. 2. Query used to search a WOS database

A structured search strategy was used to retrieve relevant texts from the WOS database for a systematic review. The search term combined the term "portfolio project" with a set of technology-related keywords connected by Boolean operators. Specifically, "portfolio project" was linked using the AND operator to a set of terms related to artificial intelligence and its subfields, as shown in Fig. 2. These terms included "AI", "artificial intelligence", "machine learning", "deep learning", "reinforcement learning", "natural language processing" and "neural network", all connected using the OR operator. This combination ensured the inclusion of studies that addressed the topics of project portfolios within the context of different technologies related to artificial intelligence, thereby increasing the comprehensiveness of the review. As a result, 73 studies were found, of which one article was in Russian and was excluded, and 4 were review articles, as mentioned above, and 44 titles were examined in detail, the results of which will be presented below.

In this study, four main criteria were considered when reviewing the relevant literature. These criteria served as the basis for analyzing and comparing the approaches adopted in previous research. The first criterion focuses on the algorithms and AI methods used in the studies and highlights the computational techniques and intelligent models that have been used to address complex decision-making processes. The second criterion emphasizes the solution methods for solving the proposed optimization models in the context of the project portfolio problem and examines the exact and heuristic approaches as well as the combinatorial techniques used to achieve effective solutions. The third criterion is related to the main case, which represents the reference scenario or benchmark problem used to validate the applicability and performance of the models under study. Finally, the fourth criterion examines the main objectives of the studies and clarifies the specific goals pursued by the researchers, such as maximizing efficiency, balancing resource allocation, or minimizing risks.

Each of these four criteria is examined in detail to provide a comprehensive understanding of the research landscape. Their interrelationships and specific features are visually summarized and organized in Fig. 4, which illustrates the framework guiding this review.

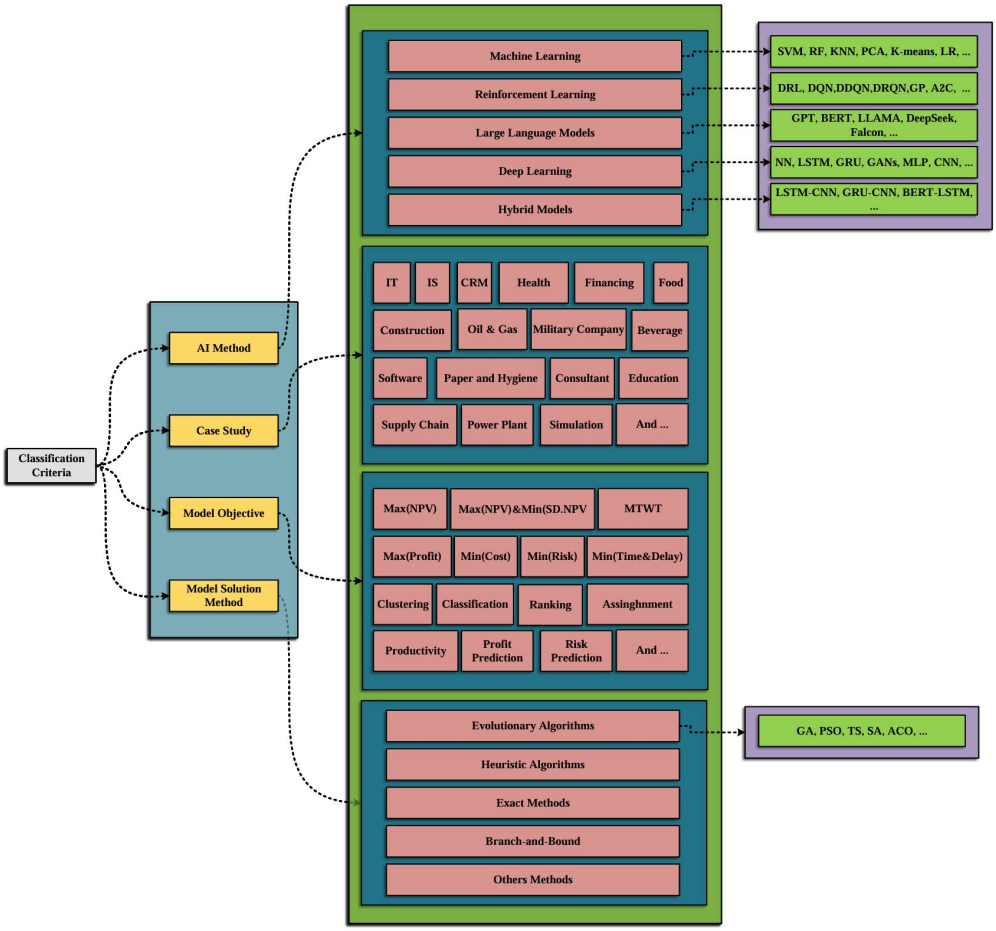

Fig. 4. Criteria for literature review

4. Literature Review

This section presents a comprehensive review of 42 selected articles after screening the extracted articles. In recent years, the integration of AI techniques into project portfolio analysis and management and decision-making frameworks has attracted considerable attention in both academia and industry. Numerous studies have investigated the application of models such as ANN, RNN, and hybrid systems, along with specialized algorithms, in various domains including IT management, oil and energy, and research and development projects. This growing body of literature represents a concerted effort to increase the accuracy, efficiency, and intelligence of cost-benefit analysis, project planning, and performance evaluation tasks. The dataset collected for this review encompasses a wide range of scholarly contributions, and citations indicate the relative impact of each study. By categorizing articles by AI methods, case study areas, and outcome types (e.g., cost-benefit, benefit-only), the dataset reveals both methodological trends and thematic changes over time. For example, earlier work often relied on conventional neural networks, while more recent studies increasingly favor complex, hybrid architectures. This development highlights a growing research landscape in which AI is not only a computational tool but also a strategic enabler for solving multifaceted project-related challenges. This literature map forms the basis of a comprehensive review that aims to synthesize current approaches, highlight methodological innovations, and identify future research opportunities in the evaluation of AI-supported projects. The reviewed articles, along with their titles and year of publication, are listed in Table 2.

We will continue to examine these studies. In a study, April et al. (2001) discussed recent practical applications created by integrating methods such as bounded search, sparse search, mixed integer programming, and neural networks in combination with simulation. Notable applications include project portfolio optimization and improved customer relationship management. Tselios et al. (2012) introduced a neural network–based method for addressing the project portfolio management problem. Their case study focused on a collection of IT projects competing for limited resources. To tackle this, they designed a multi-objective system model by framing the problem as a workshop scheduling task and implementing it through a recurrent neural network. Furthermore, they generated an initial solution by adapting a greedy algorithm.

Table 2
List of articles reviewed

No.	Article	Title
1	Tselios et al. (2013)	RNN Modelling for Bi-Objective MPM Job Shop Scheduling Problem
2	Tselios, et al. (2012)	The Weighted Tardiness as Objective Function of a RNN Model for the Job Scheduling Problem
3	Diaz et al. (2020)	Shipbuilding Supply Chain Framework and Digital Transformation: A Project Portfolios Risk
4	April et al. (2001)	Simulation/Optimization Using "Real-World" Applications
5	Bai et al. (2024)	GA-BP Neural Network Modeling for Project Portfolio Risk Prediction
6	April et al. (2004)	New Advances and Applications Marrying Simulation Optimization
7	Costantino et al. (2015)	Project Selection in Project Portfolio Management: An Artificial Neural Network Model Based on Critical Success Factors
8	Relich & Pawlewski (2017)	A Fuzzy Weighted Average Approach for Selecting Portfolio of New Product Development
9	Faezy Razi & Hooman Shariat (2017)	A Hybrid Grey Based Artificial Neural Network and C&R Tree for Project Portfolio Selection
10	Bai et al. (2024)	Measurement Of Project Portfolio Benefits with A GA-BP Neural Network Group
11	Bai et al. (2024)	A Pruned GA-BPNN Model for Project Portfolio Benefit Evaluation Considering Ambidexterity
12	Tselios & Savvas (2015)	Analysis Of the Results Obtained by Intelligent Method for Project Portfolio Scheduling
13	Moon et al. (2023)	Empirical Study of an Artificial Neural Network for a Manufacturing Production Operation
14	Tian et al. (2022)	Modeling for Project Portfolio Benefit Prediction via a GA-BP Neural Network
15	Tselios et al. (2015)	Integrated Intelligent Method for Solving Multi-Objective MPM Job Shop Scheduling Problem
16	Liu (2022)	Impact of Digital Transformation of Engineering Enterprises on Enterprise Performance Based on Data Mining and Credible Bayesian Neural Network Model
17	Bai et al. (2024)	Research and Development Project Portfolio Benefit Prediction: An Improved Backpropagation Neural Network-Based Approach
18	Wang (2018)	An Analysis of the Optimal Customer Clusters Using Dynamic Multi-Objective Decision
19	Nonino (2017)	Project Selection Frameworks and Methodologies for Reducing Risks in Project Portfolio Management
20	Bai et al. (2023)	Assessing Project Portfolio Risk via an Enhanced GA-BPNN Combined With PCA
21	Golghamat Raad et al. (2020)	Selecting A Portfolio of Projects Considering Both Optimization and Balance of Sub-Portfolios
22	Jang (2019)	A Decision Support Framework for Robust R&D Budget Allocation Using Machine Learning and Optimization
23	Chen et al. (2024)	A Multi-Skilled Staff Scheduling and Team Configuration Optimization Model for Artificial Intelligence Project Portfolio Considering Competence Development and Innovation-Driven
24	Shafiabady et al. (2023)	Using Artificial Intelligence (AI) To Predict Organizational Agility
25	Saravanan & Sangeetha (2022)	African Buffalo Optimized Multinomial SoftMax Regression Based Convolutional Deep Neural Network for Software Fault Prediction
26	Riekki & Mämmelä (2021)	Research And Education Towards Smart and Sustainable World
27	Araújo et al. (2023)	Technology Selection and Ranking: Literature Review and Current Applications in Oil & Gas Industry
28	Zaidouni et al. (2024)	A Sugeno ANFIS Model Based on Fuzzy Factor Analysis for IS/IT Project Portfolio Risk
29	Agrawal et al. (2025)	Portfolio Scenarios for Interrelated Projects
30	Black et al. (2024)	Applying Experienced-Based Co-Design Principles to Improve Digital Health Demand Management Processes in a Large Metropolitan Multi-Hospital Health System
31	Mo et al. (2020)	Automated Staff Assignment for Building Maintenance Using Natural Language Processing
32	H. Chen et al. (2024)	A Robust Human–Machine Framework for Project Portfolio Selection
33	Elnabwy et al. (2024)	An Integrated Machine Learning Approach for Evaluating Critical Success Factors Influencing Project
34	Koivisto (2022)	Gamification of Project Business Studies
35	Saiz and Calvet (2025)	Combining LLMs and Simheuristics: An Application to the Project Portfolio Selection Problem
36	Cruz-Reyes et al. (2015)	Reduction Of Decision Rules for Project Explanation on Public Project Portfolio
37	Andrade et al. (2021)	Use of Data Analytics Tools for Increased Efficiency in the Internal Audit Project Portfolio
38	Khalili-Damghani et al. (2013)	A Hybrid Fuzzy Rule-Based Multi-Criteria Framework for Sustainable Project Portfolio Selection
39	ForouzeshNejad (2024)	A Hybrid Data-Driven Model for Project Portfolio Selection Problem Based on Sustainability and Strategic Dimensions: A Case Study of the Telecommunication Industry
40	Shafi et al. (2017)	Scenario-Based Multi-Period Program Optimization for Capability-Based Planning Using Evolutionary Algorithms
41	Klein et al. (2022)	An analysis of the Clinical and Translational Science Award pilot project portfolio using data from Research Performance Progress Reports
42	Soleymani et al. (2024)	Simulation Of Autonomous Resource Allocation Through Deep Reinforcement Learning-Based Portfolio-Project Integration
43	Tsaramirsis et al. (2022)	A Modern Approach Towards an Industry 4.0 Model: from Driving Technologies to Management

Tselios et al. (2013) proposed a recurrent neural network–based solution for the shop floor scheduling problem involving multi-purpose machines. While this type of job shop scheduling problem (JSSP) is traditionally applied in manufacturing settings, it can also serve as a framework for modeling project portfolio management.

Their work expanded a dual-objective system model derived from JSSP and implemented it using two interconnected recurrent neural networks. Tselios & Savvas (2015) explored multi-objective models grounded in intelligent methods and designed to reflect real-world project scenarios. They assessed these approaches by statistically testing selected research questions, with several yielding positive results that demonstrated the effectiveness of the overall solution method.

April et al. (2004) examined innovative real-world applications built through the integration of simulation with techniques such as bounded search, sparse search, mixed integer programming, and neural networks. The study highlights use in areas like project portfolio optimization and supply chain management. In their study, Tselios et al. (2015) introduced a hybrid method for addressing a bi-objective optimization problem involving makespan and total weighted delay. The approach unfolds in three phases: first, a GA generates an initial pool of solutions; second, these solutions are provided as inputs to RNNs; and finally, the RNN outputs are refined using adaptive learning rates combined with a search procedure resembling Tabu Search to enhance the recursive solutions.

The study by Faezy Razi and Hooman Shariat (2017) proposes a hybrid framework for project portfolio selection that combines artificial neural networks, gray relational analysis, decision trees, regression techniques, and genetic algorithms. Drawing on 49 PMBOK indicators, the model highlights key factors such as scope management, the project charter, the project management plan, stakeholder involvement, and risk. Results indicate that applying gray relational analysis with neural network–derived weights yields more effective portfolio ranking outcomes. To ensure robustness, the authors also employ sensitivity analysis, which validates the model's accuracy and enhances the reliability of decision-making. Wang (2018) examines the food and beverage (F&B) sector in a type M competitive environment using a project portfolio perspective for customer clustering. The approach seeks to reduce inter-cluster interactions while strengthening internal cluster consistency to enhance decision-making. The study's results address the challenge of dispersed intra-group structures in clustering and demonstrate how the method can facilitate dynamic, multi-objective service decisions, offering strategic insights for industries operating under uncertainty.

Shafi et al. (2017) introduce a hybrid approach that combines multi-objective evolutionary algorithms (MOEAs) with reinforcement learning to optimize project portfolios in the defense sector across multiple planning horizons and uncertain conditions. The method adaptively manages the trade-off between strategic risk reduction and cost efficiency over the long term. Validated through the Australian Defense Capability Plan, the framework demonstrates superior performance compared to exploratory baselines and offers a broadly applicable solution for long-term project portfolio optimization beyond defense contexts. Relich and Pawlewski (2017) proposed a fuzzy weighted average model integrated with neural networks to support new product portfolio selection under uncertainty. The evaluation framework considers criteria such as marketing, team capability, performance, risk, and strategic alignment. While the fuzzy method enables project ranking, the neural network component enhances performance prediction and decision precision. A case study illustrates the model's effectiveness in guiding choices for new product development.

Mo et al. (2020) developed a machine learning approach leveraging NLP to enhance staffing allocation in construction projects. Their model processes service request texts to automatically determine staffing assignments and priorities. Using a dataset of over 82,000 maintenance records from 60 university buildings collected over three years, the approach achieved 77% accuracy in staffing predictions and 88% in priority classification, emphasizing the significance of stop words and punctuation in text analysis. Zaidouni et al. (2024) introduce ANFIS-OPR, a hybrid framework designed to predict overall risk in IS/IT project portfolios. The method combines fuzzy factor analysis (FFA) to reduce high-dimensional fuzzy risk data with an adaptive neuro-fuzzy Sugeno inference system (ANFIS) to enhance strategic interpretability. By incorporating expert insights from project management offices (PMOs) into fuzzy rule sets, the model aligns risk predictions with organizational objectives. A case study demonstrates its effectiveness, achieving a low RMSE of 0.108 and showcasing strong potential for monitoring and mitigating portfolio-level risks.

Andrade et al. (2021) investigate how data analytics tools are reshaping internal audit project portfolios in response to the growth of electronic transactions. The study highlights that analytics enhance data mining, modeling, and analysis, providing audit managers with stronger decision support. Results indicate that adopting these tools decreases workload, broadens result coverage, and improves audit efficiency. Overall, data analytics contributes to more effective project planning, resource allocation, agility, and traceability, reinforcing the future role of internal audit. Tian et al. (2022) propose a GA-BPNN model to overcome the shortage of reliable methods for forecasting project portfolio benefits (PPBs). The approach combines a genetic algorithm with backpropagation neural networks, enhancing prediction accuracy through optimization. A numerical case study illustrates its effectiveness, achieving an average accuracy of 98.64%, markedly outperforming a standard BPNN. The results contribute to project portfolio management research and offer practitioners a powerful tool for PPB forecasting.

Chen et al. (2024) investigate the optimization of R&D team configurations for AI product development with the aim of enhancing employee competence and team diversity. They propose a three-objective nonlinear mixed integer programming model that accounts for learning effects and heterogeneous efficiency in assessing skills and backgrounds. By applying NSGA-II, the study identifies Pareto-optimal solutions and compares them with MOPSO results, supplemented by sensitivity analysis. A healthcare AI product case study validates the approach, offering practical insights for firms seeking to strengthen their R&D capabilities. Costantino et al. (2015) explore how incorporating critical success factors (CSFs) into project portfolio management can improve project selection. They develop a decision support system that forecasts project performance at the

selection stage, employing an ANN to classify risk levels based on historical project data. By integrating project managers' expertise with CSFs, the approach strengthens strategic alignment and mitigates the likelihood of project failure.

Chen et al. (2024) tackle the project portfolio selection and scheduling (PPSS) problem, an NP-hard challenge complicated by multiple constraints and individual preferences. They introduce a qualitative evaluation method to streamline and reduce the cost of assessing project value. Building on this, a preference-based deep reinforcement learning approach is employed to identify optimal project subsets and scheduling plans. Experimental results demonstrate that the proposed method outperforms traditional and heuristic algorithms in both accuracy and effectiveness. Jang (2019) introduced a decision support framework for R&D budget allocation aimed at maximizing expected research outcomes. The approach integrates a machine learning model to predict R&D output with a robust optimization method to handle uncertainty. Applied to a Korean national R&D program, the framework increased research output by 13.6% compared to the actual budget allocations.

Koivisto (2022) explores the use of gamification in education to enhance skills in PPM. Although some critics highlight potential stress and competition, gamification has been found to boost engagement, problem-solving, collaboration, and communication. Feedback from graduate students was analyzed using both manual and machine-learning–based sentiment analysis, revealing predominantly positive responses. These findings suggest that gamification is an effective method for teaching PPM and improving decision-making skills in managing diverse project portfolios. Elnabwy et al. (2024) investigate the critical success factors (CSFs) influencing the adoption of PPM in the construction sector. Based on an expert-validated questionnaire and machine learning analysis, the study highlights project size, PPM tools, and resource allocation as primary success drivers. Among the tested models, the Extra Tree Classifier (ETC) delivered the highest prediction accuracy. The results offer practical guidance for construction firms to strengthen PPM adoption, optimize resource use, and improve project performance.

Diaz et al. (2020) propose a framework for evaluating project portfolio risk in the military shipbuilding industry during digital transformation. The method combines ANN with Monte Carlo simulation to analyze benefits, risks, and cost–benefit trade-offs. A theoretical case study illustrates the framework's effectiveness in optimizing resource allocation and reducing risk exposure. Saiz & Calvet (2025) present Generative Heuristics, a framework that integrates LLMs with metaheuristic algorithms to support project portfolio selection. The method combines quantitative optimization through simulation algorithms with qualitative insights derived from LLMs. Applied to the EU LIFE program with real project data, the approach demonstrates its ability to balance financial measures such as Net Present Value (NPV) with strategic partnership considerations.

Bai, Wei, et al. (2024) propose a hybrid method for predicting project portfolio risk (PPR) that integrates GA-BPNN with entropy-trapezoidal fuzzy numbers. The model estimates PPR impact by incorporating both the probability of risk events and their consequences within interdependent projects. Experimental results demonstrate a prediction accuracy of 97.8%, significantly exceeding that of conventional BPNN models. Nonino (2017) highlights the strategic role of project selection in building a balanced portfolio, with particular attention to risks and uncertainties in project portfolio management. The work reviews both traditional and innovative selection frameworks and introduces an ANN–based approach to support project evaluation. This model assists managers in balancing risks, uncertainties, and critical success factors during the selection process.

Bai, et al. (2024) present a project portfolio benefits (PPB) measurement model based on a Genetic Algorithm–BP Neural Network Group (GA-BPNNG) to enhance portfolio benefits management. The model incorporates group learning, collaboration, and information sharing to account for financial, non-financial, and synergy-related benefits. Compared to standard BPNN and GA-BPNN approaches, it achieves substantial error reductions of 94% and 83%, respectively. The results highlight its strong nonlinear fitting capability and offer managers a practical, scalable tool for PPB evaluation. Moon et al. (2023) examine inventory management challenges at a Korean cable manufacturer through an empirical study. They developed two multilayer perceptron (MLP) neural network models using 23,226 data samples to predict production days and product delays. The models achieved strong accuracy ($R^2 = 0.919$ and 0.773) and revealed a hierarchy of resource importance, offering data-driven insights to help SMEs enhance inventory planning and reduce stagnation.

Bai, Zhang, et al. (2024) develop a modified inverse immune-propagation genetic algorithm (RIGA-BPNN) based neural network to predict R&D PPBs under conditions of uncertainty and complexity. The model integrates benefit evaluation and synergy quantification while enhancing BPNN optimization through increased multi-proportionality, crossover, and mutation rates. Experimental results show high prediction accuracy (99.26%) and faster convergence compared to standard BPNN and IGA-BPNN models. Riekki and Mämmelä (2021) propose a vision for steering ICT research and education toward a smart and sustainable future. The study highlights intelligent systems capable of sensing, decision-making, and acting to address societal, industrial, and environmental challenges. Central elements include artificial intelligence, feedback mechanisms, human oversight, resource efficiency, and a holistic approach to complex systems. The paper provides guidance for planning research initiatives, project portfolios, and educational programs while fostering creativity, evolutionary development, and interdisciplinary coherence.

Bai et al. (2023) propose a PCA-IGA-BPNN model for evaluating project portfolio risk (PPR) while accounting for project interdependencies. The approach employs fuzzy logic and principal component analysis (PCA) to preprocess and reduce assessment data, and an improved genetic algorithm (IGA) to optimize BPNN parameters. Experimental results demonstrate

high accuracy (98.6%) and outperform conventional neural network and machine learning approaches. Soleymani et al. (2024) tackle resource allocation challenges in multi-project construction planning through an autonomous resource allocation (ARA) model. The approach leverages DRL agents, including dual deep Q-networks with experience replay, to optimize resource allocation using IoT-generated data. Results indicate that DRL efficiently manages complex resource interactions and adapts to changing conditions without requiring retraining.

Liu (2022) examines how digital transformation (DT) influences corporate performance within the context of the digital economy. The study proposes a predictive framework for project portfolios that integrates data mining (DM) with a Bayesian neural network. By analyzing quantitative financial data, the model forecasts corporate performance, with accuracy improving as the sample size grows. The results confirm the value of combining data mining with neural networks for performance prediction. Golghamat Raad et al. (2020) address project portfolio selection with the goal of maximizing overall portfolio profit while maintaining sub-portfolio efficiency. Their approach applies data mining to cluster projects and employs multi-criteria decision-making (MCDM) methods to weight ranking criteria. They propose a multi-objective optimization model solved with the NSGA-II algorithm. The hybrid framework enables portfolio selection that accounts for strategic alignment, cost, and risk.

Shafiabady et al. (2023) investigate how AI can be applied to predict organizational agility in the post-pandemic era. Using survey data from 44 Australian industry professionals, they tested machine learning models including SVM, KNN, and random forest. The findings indicate that RF and KNN achieved strong predictive accuracy across multiple scenarios, while also identifying critical enablers of agility and barriers such as weak executive engagement and low organizational maturity. Agrawal et al. (2025) critique traditional portfolio selection methods for overlooking practical portfolios that balance both quantitative and qualitative factors. To address this gap, they propose a compatibility matrix that captures project interactions such as exclusivity and complementarity. This approach produces a comprehensive set of feasible portfolio scenarios free from incompatible projects. The framework offers managers a flexible and practical tool that can be applied on its own or alongside existing optimization techniques.

Araújo et al. (2023) conducted a systematic literature review on project selection and ranking approaches within the oil and gas (O&G) sector. The review discusses methods such as mathematical programming, artificial intelligence, and decision theory, as well as commonly used evaluation criteria. The findings reveal a scarcity of studies in this domain, particularly regarding the assessment of new technologies, with notable gaps such as the neglect of equipment reliability. The authors propose a research agenda that encourages combining methods and incorporating criteria like risk and reliability, especially in R&D contexts. Cruz-Reyes et al. (2015) tackle the problem of generic project portfolio selection under multiple objectives using a multi-criteria optimization framework. Instead of yielding a single solution, their method produces Pareto-optimal portfolios and applies simplified decision rules for recommendations. To reduce complexity, they propose a hybrid approach based on rough set theory that integrates genetic algorithms with exact methods. This improves interpretability, allowing decision makers to better understand project acceptance or rejection while preserving high classification accuracy.

Bai et al. (2024) propose an enhanced PPB evaluation model that explicitly incorporates synergies and ambidexterity, factors often neglected in prior studies. They develop a modified backpropagation genetic algorithm neural network (P-GA-BPNN) to improve evaluation accuracy and minimize structural redundancy. Comparative experiments against BPNN, GA-BPNN, and SVM confirm the model's superior performance, robustness, and fitting accuracy. The approach offers organizations a practical decision support tool for managing and enhancing PPB. Saravanan & Sangeetha (2022) present the African Buffalo-Optimized Softmax Polynomial Regression Convolutional Deep Neural Learning (ABOMSR-CDNL) model for software error prediction. This approach integrates event log data with software code in a deep neural framework, using optimized parameters to identify error causes at early stages. Incorporating Softmax polynomial regression within hidden layers enhances accuracy, reduces false positives, and accelerates error detection. The results demonstrate greater reliability and efficiency compared to traditional software quality assurance methods.

Khalili-Damghani et al. (2013) propose a rule-based hybrid fuzzy multi objective framework for sustainable project portfolio selection. The framework combines data mining, data envelopment analysis (DEA), and evolutionary algorithms to assess portfolio suitability while balancing accuracy and complexity. A genetics-based machine learning (GBML) approach is used for comparison, and results from a real-world financial services case demonstrate the framework's superior accuracy and interpretability. ForouzeshNejad (2024) proposes a hybrid data-driven framework for project portfolio selection in the telecommunications sector. Project evaluation criteria are determined using expert surveys and the fuzzy best-worst method (FBWM), identifying key factors such as capital requirements, revenue, labor, energy reduction, and market share. Annual project performance is assessed through DEA and predicted using machine learning models, including random forest and support vector regression. Results indicate that random forest delivers the highest prediction accuracy, offering managers an effective tool for more efficient project selection.

Black et al. (2024) employed experience-based collaborative design (EBCD) within an implementation framework to enhance digital health demand management across a multi-hospital system. Through qualitative analysis, they identified barriers such as fragmented information, decentralized processes, and ambiguous governance. Together with stakeholders, they developed interventions including a centralized intake workflow, a project lifecycle tracking tool, and a weighted scoring model for prioritization. The study demonstrates how EBCD fosters flexible, scalable solutions for managing digital health project portfolios, ultimately advancing efficiency and responsiveness in healthcare innovation. The study by Klein et al. (2022)

investigates the challenges of accessing administrative data in Clinical Trials and Translational Science Awards (CTSA) projects, which report over 600 trials annually. To address this, the authors developed a semi-automated script to extract trial information from research progress reports and applied a machine learning model to classify projects by scientific content. Their findings demonstrate the wide scientific diversity of the CTSA trial portfolio and reveal overlaps in research interests across centers. The study underscores both the difficulties of extracting unstructured data and the benefits of structured trial data for portfolio management, collaboration, and stakeholder engagement.

Fig. 5 schematically shows an overview of these studies, including criteria for the number of citations, trends in the number of articles published on the topic under study, word clouds of selected articles reviewed, word clouds of journals, word clouds of case studies, and a brief classification of the study objectives.

Fig. 5. Graphical display of additional information from studies conducted. (a): Number of articles per year. (b): Highly cited articles. (c): Journals word cloud. (d):AI method word cloud. (e): Case study word cloud. (f): Objective function classification.

Fig. 6-(a) shows the evolution of research on project portfolio management, including AI tools and models. From 2001 to 2015, published papers were sparse and relatively rare, indicating an exploratory phase when the topic had not yet gained a central place in academic discourse. A steady increase was observed between 2016 and 2020, coinciding with the adoption of advanced computational methods and the growing interest in AI. The most significant increase occurred from 2022 to 2024, when access to better technologies and interdisciplinary collaboration led to an increase in scientific output. Fig. 6-(b) shows a citation-based assessment of the papers, identifying the most influential studies in the field. Costantino et al. stand out with over 300 citations, while April et al. (2001) and Tsaramirsis et al. (2022) follows closely with 150–180 citations. A second

group of researchers, including Khalili-Damghani, Zhang, and Mu, also show significant impact with 90–140 citations. Although many other authors have received fewer individual citations, their collective contribution is still significant, ensuring diversity and broadening of the research discourse.

Fig. 6-(c) shows a wide range of publication journals in the journal analysis, including EEE Transaction, EEEE Access, Journal of Enterprise Information Management, Engineering Applications of Artificial Intelligence, Kybernetes, Mathematics, International Journal of Production Research , International Journal of Project Management, Procedia Manufacturing, Security and Communication Networks and etc.

According to Fig. 6-(d), in terms of methodology, a wide range of AI techniques have been applied to project portfolio management. Neural networks such as ANN, RNN, BP, RL, MLP and LSTM are most commonly used for performance prediction and time series data management. Fuzzy logic, genetic algorithms, and evolutionary optimization are also prominent, often combined with machine learning approaches to tackle multi-objective problems. Other models, including Bayesian methods, support vector machines, and deep reinforcement learning, further enrich the methodological diversity. Hybrid and ensemble approaches are increasingly dominant, reflecting the complexity and uncertainty of real-world project portfolio management.

Fig. 6-(e) shows a case study of the papers. The case studies show how these models are applied in different industries. The IT and software sectors are common, highlighting their role as early adopters of advanced tools. Construction, infrastructure, and energy projects particularly in oil, gas, and power also feature frequently due to their high resource demands and risks. The defense, healthcare, and food industries extend the scope of applications beyond purely economic ones. At the regional level, countries such as China, Iran, and South Korea are emerging as focal points, reflecting their rapid industrial development and investment in large projects. Finally, in Fig. 6-(f), the analysis of objectives shows the dominance of multi-criteria approaches that integrate cost and benefit considerations. Approximately half of the studies adopt this balanced view, consistent with modern portfolio theories that emphasize trade-offs between investments, benefits, and risks. Some research focuses exclusively on benefits such as financial returns or strategic alignment, while others, particularly in public or defense projects with tight budgets, prioritize cost efficiency. A small number of studies do not clearly classify objectives, indicating gaps for future methodological improvements. Overall, this trend reflects a shift from cost-based assessments to integrated frameworks that better capture organizational complexity and evolving market conditions.

4. Research Results

In this part of the paper, we provide a detailed summary of the findings derived from the review of the studies listed in Table 2. The discussion is structured around four main dimensions. First, attention is given to the algorithms and artificial intelligence techniques that have been applied to address the project portfolio management problem. Second, the types and characteristics of case studies employed in the reviewed works are highlighted. Third, the objectives pursued in these articles are classified according to their research orientation and purpose. Finally, the approaches proposed for tackling both single-objective and multi-objective project portfolio optimization are examined, with an emphasis on the methodological diversity adopted across the literature.

4.1. Applications of Artificial Intelligence Algorithms and Methods in Portfolio Project Problems

Table 3 presents a detailed synthesis of how various AI techniques and algorithms have been applied within the domain of project portfolio management PPM. The classification illustrates the broad spectrum of methodological approaches that researchers have employed over time. Earlier studies often relied on conventional machine learning models, for example, neural networks, decision trees, and clustering methods. More recent research, however, shows a shift toward advanced paradigms such as reinforcement learning, deep learning architectures, and, most recently, large language models. By organizing these methods systematically, the table not only reveals the chronological evolution of AI utilization in PPM but also sheds light on emerging directions and potential future research opportunities in this field.

Table 3 shows that models, especially ANN and RNN, were dominant in the early 2000s and mid-2010s, serving as essential tools for addressing optimization and forecasting tasks in project portfolio decision-making. Over time, the scope has expanded to include adaptive and hybrid techniques, such as fuzzy inference systems and ensemble learning, which improve flexibility and interpretability in complex project portfolio environments. A notable trend is the gradual rise of RL and DL methods in recent years. These paradigms represent a shift toward dynamic, data-driven problem solving that enables models to learn adaptive strategies and manage large-scale project datasets more effectively. Furthermore, the inclusion of advanced evolutionary and bio-inspired algorithms (e.g., ENSGA-II, GBML, and RIGA-BPNN) represents a continuing effort to enhance optimization capabilities through meta-heuristic approaches. Recently, the literature has begun to incorporate NLP techniques, LLMs, and ensemble frameworks. This development highlights a move toward more integrated and intelligent systems capable of handling unstructured information, enhancing decision support, and providing more robust recommendations for the project portfolio. The existence of studies using hybrid and multi-model architectures further reflects the growing recognition that single methods are often insufficient to understand the multifaceted nature of project portfolio problems. In summary, this classification represents a clear evolution from traditional AI-based optimization methods to advanced, hybrid, and large-scale learning frameworks. This transition reflects not only technological advances in AI, but also the increasing complexity of project portfolio challenges that require more adaptive, interpretable, and scalable solutions.

Table 3
Classification of Artificial Intelligence Algorithms and Techniques

No.	Author's/Year	ANN	RNN	AL	GRA	CCM	RL	ANFIS	LR	NLP	ACLA	BPNN	ENSGA-II	DL	DRL	Stacked Ensemble	N-gram	ETC	LLMs	BPNNG	MLP	RIGA-BPNN	PCA	BNN	K-means	ABOMSR-CDNL	GBML	Others
1	April et al., (2001)	✓																										
2	Tselios et al., (2012)		✓																									
3	Tselios et al., (2013)		✓																									
4	Tselios & Savvas, (2015)		✓																									
5	April et al., (2004)	✓																										
6	Tselios et al., (2015)		✓	✓																								
7	Faezy Razi & Hooman Shariat, (2017)	✓			✓																							
8	Wang, (2018)					✓																						
9	Shafi et al., (2017)						✓																					
10	Relich & Pawlewski, (2017)	✓						✓	✓																			
11	Mo et al., (2020)									✓																		
12	Zaidouni et al., (2024)							✓																				
13	Tian et al., (2022)											✓																
14	Chen et al., (2024)												✓															
15	Andrade et al., (2021)										✓																	
16	Costantino et al., (2015)	✓																										
17	Chen et al., (2024)													✓	✓													
18	Jang, (2019)															✓												
19	Koivisto, (2022)																✓											
20	Elnabwy et al., (2024)								✓									✓										
21	Diaz et al., (2020)	✓																										
22	Saiz & Calvet, (2025)																			✓								
23	Bai, Wei, et al., (2024)											✓																
24	Nonino, (2017)	✓																										
25	Bai, An, et al., (2024)																			✓								
26	Moon et al., (2023)																				✓							
27	Bai, Zhang, et al., (2024)											✓										✓						
28	Riekki & Mämmelä, (2021)																											✓
29	Bai et al., (2023)											✓										✓	✓					
30	Soleymani et al., (2024)														✓													
31	Liu, (2022)																						✓					✓
32	Golghamat Raad et al., (2020)	✓																			✓				✓			
33	Shafiabady et al., (2023)								✓																			✓
34	Agrawal et al., (2025)																											✓
35	Araújo et al., (2023)	✓																						✓				✓
36	Cruz-Reyes et al., (2015)																											✓
37	Bai, Liu, et al., (2024)											✓																✓
38	Saravanan & Sangeetha, (2022)																									✓		
39	Khalili-Damghani et al., (2013)																										✓	
40	ForouzeshNejad, (2024)		✓						✓												✓							✓
41	Black et al., (2024)																											✓
42	Klein et al., (2022)																											✓

Note that in Table 3 the following notations are used:

GRA: Grey Relational Analysis, AL: Adaptive Learning, CCM: Clustering based on Correlation Matrix, ACLA: Audit Command Language Analytics, BPNN: backpropagation neural network, ENSGA-II: Enhanced Non-Dominated Genetic Algorithm, ETC: Extra Trees Classifier, MLP : Multilayer Perceptron , RIGA-BPNN: refined immune genetic algorithm coupling backpropagation neural network, BNN: Bayesian neural network, ABOMSR-CDNL: African Buffalo-Optimized Softmax Polynomial Regression–Convolutional Deep Neural Learning, GBML: genetics-based machine learning.

4.2. Case Studies of AI Applications in Project Portfolio Problems

Table 4 summarizes the case study domains in which artificial intelligence methods have been applied to project portfolio management. The classification illustrates the diversity of application areas, ranging from traditional business functions such as customer relationship management and financing to more specialized contexts including healthcare, defense, telecommunications, and environmental sustainability. This overview allows for identifying the breadth of real-world implementation and highlights how AI-driven approaches have been adapted to different industrial and organizational needs.

The case studies demonstrate how the integration of artificial intelligence with project portfolio management has evolved across multiple domains. Early applications mainly focused on areas such as customer relationship management, financing, and information technology, where project portfolios could be structured and evaluated using well-defined criteria. In these contexts, AI methods supported portfolio managers by improving prioritization, resource allocation, and performance forecasting, thereby enhancing the overall effectiveness of portfolio-level decision-making. As research advanced, AI-enabled portfolio approaches expanded into more complex and uncertain environments, including healthcare, defense, energy, and telecommunications. In these cases, the project portfolio perspective provided a systematic framework for managing diverse initiatives, while AI techniques offered the computational intelligence required to handle uncertainty, dynamic conditions, and large-scale datasets. This synergy allowed organizations to move beyond single-project optimization and to achieve balanced outcomes across entire portfolios. Moreover, recent contributions highlight the relevance of AI in sustainability-oriented portfolios, such as environmental and climate-related projects. Here, project portfolios often involve conflicting objectives, long-term impacts, and heterogeneous stakeholders. AI methods combined with portfolio-based thinking facilitate the identification of trade-offs and the development of adaptive strategies, ensuring that decision-makers can pursue both efficiency and sustainability goals. It is also notable that a portion of the literature adopts simulation-based or conceptual case studies rather than focusing on a specific industry. These works emphasize methodological innovations, exploring how portfolio-oriented frameworks and AI algorithms can be jointly leveraged to optimize multi-project environments. Hybrid approaches that integrate statistical data, questionnaires, and domain-specific simulations further highlight the adaptability of AI when combined with portfolio perspectives. In summary, the case study classification underscores the value of merging project portfolio concepts with artificial intelligence. While the portfolio perspective ensures a structured and strategic orientation across multiple projects, AI provides the analytical and predictive power to manage complexity, uncertainty, and dynamic change. Together, they form a robust foundation for advancing decision-support systems across a wide spectrum of organizational and societal challenges. The case studies demonstrate how the integration of artificial intelligence with project portfolio management has evolved across multiple domains. Early applications mainly focused on areas such as customer relationship management, financing, and information technology, where project portfolios could be structured and evaluated using well-defined criteria. In these contexts, AI methods supported portfolio managers by improving prioritization, resource allocation, and performance forecasting, thereby enhancing the overall effectiveness of portfolio-level decision-making. As research advanced, AI-enabled portfolio approaches expanded into more complex and uncertain environments, including healthcare, defense, energy, and telecommunications. In these cases, the project portfolio perspective provided a systematic framework for managing diverse initiatives, while AI techniques offered the computational intelligence required to handle uncertainty, dynamic conditions, and large-scale datasets. This synergy allowed organizations to move beyond single-project optimization and to achieve balanced outcomes across entire portfolios.

Moreover, recent contributions highlight the relevance of AI in sustainability-oriented portfolios, such as environmental and climate-related projects. Here, project portfolios often involve conflicting objectives, long-term impacts, and heterogeneous stakeholders. AI methods combined with portfolio-based thinking facilitate the identification of trade-offs and the development of adaptive strategies, ensuring that decision-makers can pursue both efficiency and sustainability goals. It is also notable that a portion of the literature adopts simulation-based or conceptual case studies rather than focusing on a specific industry. These works emphasize methodological innovations, exploring how portfolio-oriented frameworks and AI algorithms can be jointly leveraged to optimize multi-project environments. Hybrid approaches that integrate statistical data, questionnaires, and domain-specific simulations further highlight the adaptability of AI when combined with portfolio perspectives. In summary, the case study classification underscores the value of merging project portfolio concepts with artificial intelligence. While the portfolio perspective ensures a structured and strategic orientation across multiple projects, AI provides the analytical and predictive power to manage complexity, uncertainty, and dynamic change. Together, they form a robust foundation for advancing decision-support systems across a wide spectrum of organizational and societal challenges.

Table 4
Case studies combining the two fields of AI and PPM

No.	Author's/Year	CRM	Financing	IT	Supply Chain	Power Plant Repair	Food and Beverage	Defense Force	New Product Development	University Operations	IS	Paper and Hygiene	Consultant company	Healthcare	Statistical data	Construction	Academic research	Environment and Climate	Questionnaire	Cable	R&D projects	Education	Digital Economy	Oil & Gas	Simulation	Hybrid	telecommunication	Software	No Case study
1	April et al., (2001)	✓	✓																										
2	Tselios et al., (2012)			✓																									
3	Tselios et al., (2013)																												✓
4	Tselios & Savvas, (2015)																												✓
5	April et al., (2004)				✓																								
6	Tselios et al., (2015)																												✓
7	Faezy Razi & Hooman Shariat, (2017)					✓																							
8	Wang, (2018)						✓																						
9	Shafi et al., (2017)							✓																					
10	Relich & Pawlewski, (2017)								✓																				
11	Mo et al., (2020)									✓																			
12	Zaidouni et al., (2024)			✓							✓																		
13	Tian et al., (2022)												✓																
14	Chen et al., (2024)													✓															
15	Andrade et al., (2021)											✓																	
16	Costantino et al., (2015)							✓																					
17	Chen et al., (2024)														✓														
18	Jang, (2019)															✓													
19	Koivisto, (2022)																✓												
20	Elnabwy et al., (2024)															✓													
21	Diaz et al., (2020)				✓			✓																					
22	Saiz & Calvet, (2025)																	✓											
23	Bai, Wei, et al., (2024)																		✓										
24	Nonino, (2017)			✓																									
25	Bai, An, et al., (2024)															✓													
26	Moon et al., (2023)																			✓									
27	Bai, Zhang, et al., (2024)																				✓								
28	Riekki & Mämmelä, (2021)			✓																		✓							
29	Bai et al., (2023)																								✓				✓
30	Soleymani et al., (2024)																								✓				✓
31	Liu, (2022)																						✓						
32	Golghamat Raad et al., (2020)		✓																										
33	Shafiabady et al., (2023)																					✓				✓			
34	Agrawal et al., (2025)																								✓				✓
35	Araújo et al., (2023)																							✓					
36	Cruz-Reyes et al., (2015)																												✓
37	Bai, Liu, et al., (2024)												✓																
38	Saravanan & Sangeetha, (2022)																											✓	
39	Khalili-Damghani et al., (2013)																							✓					
40	ForouzeshNejad, (2024)																										✓		
41	Black et al., (2024)													✓															
42	Klein et al., (2022)													✓															

4.3. Study Objectives and Purposes

Table 5 outlines the main objectives and purposes pursued by the reviewed studies that applied artificial intelligence techniques to project portfolio management. The classification captures a broad spectrum of goals, ranging from maximizing financial metrics such as net present value (NPV) and profit to minimizing risks, uncertainties, costs, and delays. Additionally, several studies emphasize resource and budget allocation, project ranking and prioritization, and predictive analytics. This mapping provides insights into how AI has been strategically used to enhance decision-making processes in project portfolio contexts. The distribution of objectives shows that early studies primarily concentrated on financial optimization, with maximizing NPV and minimizing costs being dominant themes. These objectives reflect the traditional economic orientation of project portfolio management, where success was often evaluated by profitability and financial efficiency. AI methods were leveraged in this context to perform complex calculations, improve forecasting accuracy, and support trade-off analyses among competing projects. Over time, the scope of objectives expanded to include more dynamic and risk-sensitive dimensions such as minimizing uncertainty, reducing risk, and predicting errors or delays. This progression highlights the added value of AI in handling stochastic and complex environments, where traditional portfolio approaches may fall short. Techniques like machine learning, reinforcement learning, and data analytics enabled portfolio managers to anticipate disruptions, improve resilience, and design adaptive strategies across multiple projects. Another significant trend is the increasing attention to portfolio-level decision-making tasks, such as ranking, prioritization, project assignment, and clustering. By combining AI algorithms with portfolio frameworks, researchers created systems that not only optimize single projects but also balance trade-offs across the entire portfolio. This integration illustrates the synergy between AI's computational power and the portfolio perspective's strategic orientation. More recent contributions extend these objectives to predictive modeling, profit estimation, and productivity enhancement. For instance, some studies employ AI to support budget and resource allocation decisions, ensuring optimal use of limited capacities across diverse portfolios. Others apply predictive models for performance or error detection, reinforcing the proactive nature of AI-driven portfolio management. In summary, the classification indicates an evolution from purely financial and efficiency-driven objectives toward a broader set of strategic, predictive, and adaptive goals. The integration of AI into project portfolio management allows organizations not only to maximize value but also to mitigate risks, manage uncertainties, and ensure sustainable performance across a diverse set of projects.

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4.4. Solution methods for project portfolio problems

Table 6 presents a systematic categorization of the solution methods employed in the reviewed body of literature to tackle challenges in PPM.

The classification demonstrates the methodological richness of this research area, revealing how scholars and practitioners have drawn on a variety of computational strategies to address the complexity inherent in portfolio-level decision-making. Among the most prominent approaches are meta-heuristic algorithms such as GA, TS, and PSO which are particularly well suited for navigating large and complex solution spaces where traditional optimization methods often fall short. Alongside these, heuristic techniques provide simplified yet effective rules of thumb for generating feasible solutions in a computationally efficient manner, while exact methods continue to play an important role in ensuring mathematically optimal outcomes in more structured problem settings. The results reveal that metaheuristic algorithms have been the most widely adopted solution approach for integrating AI with project portfolio management. Among them, genetic algorithms and particle swarm optimization appear most frequently, reflecting their strength in addressing nonlinear, multi-objective, and combinatorial problems typical of project portfolio environments. These algorithms provide flexibility in navigating large solution spaces and balancing competing objectives such as cost, risk, and profitability. While metaheuristics dominate, other solution strategies also play important roles. Exact methods and heuristic approaches appear in studies that emphasize computational efficiency or situations where problem structures are more constrained. Scatter search, branch-and-bound, and OptTek-based approaches are less common but demonstrate the use of tailored algorithms when precision and mathematical rigor are required. These methods often complement AI-driven portfolio models by ensuring robustness in specific decision contexts. An emerging trend is the development of hybrid methods, combining heuristic reasoning with data-driven AI models. Such approaches aim to leverage the strengths of both sides: the interpretability and problem-specific adaptability of heuristics with the predictive and optimization capabilities of AI. This combination is particularly valuable for large-scale portfolios where traditional methods alone are insufficient.

Table 5
Key objectives of the studies conducted

No.	Author's/Year	Max(NPV)	Min(Cost)	Max(NPV)/Min(SDNPV)	Min(Time)	Min(Time)/ Min(Delay)	MTWT	Classification	Min (Uncertainty)	Min(Risk)	Max(Profit)	Ranking or prioritization	Assignment or Selection	Risk(Prediction)	Data Analytics	Profit Prediction	Max (Productivity)	Budget Allocation	Resource Allocation	Clustering	Error prediction
1	April et al., (2001)	✓																			
2	Tselios et al., (2012)				✓																
3	Tselios et al., (2013)					✓															
4	Tselios & Savvas, (2015)						✓														
5	April et al., (2004)			✓																	
6	Tselios et al., (2015)																				
7	Faezy Razi & Hooman Shariat, (2017)							✓													
8	Wang, (2018)	✓							✓												
9	Shafi et al., (2017)									✓											
10	Relich & Pawlewski, (2017)											✓									
11	Mo et al., (2020)												✓								
12	Zaidouni et al., (2024)													✓							
13	Tian et al., (2022)															✓					
14	Chen et al., (2024)																✓				
15	Andrade et al., (2021)														✓						
16	Costantino et al., (2015)									✓											
17	Chen et al., (2024)						✓														
18	Jang, (2019)																	✓			
19	Koivisto, (2022)				✓							✓							✓		
20	Elnabwy et al., (2024)																		✓		
21	Diaz et al., (2020)			✓																	
22	Saiz & Calvet, (2025)	✓																			
23	Bai, Wei, et al., (2024)													✓							
24	Nonino, (2017)									✓											
25	Bai, An, et al., (2024)										✓										
26	Moon et al., (2023)		✓																		
27	Bai, Zhang, et al., (2024)															✓					
28	Riekki & Mämmelä, (2021)																✓				
29	Bai et al., (2023)								✓	✓											
30	Soleymani et al., (2024)																		✓		
31	Liu, (2022)														✓		✓				
32	Golghamat Raad et al., (2020)										✓										
33	Shafiabady et al., (2023)																			✓	
34	Agrawal et al., (2025)												✓								
35	Araújo et al., (2023)																			✓	
36	Cruz-Reyes et al., (2015)												✓								
37	Bai, Liu, et al., (2024)										✓										
38	Saravanan & Sangeetha, (2022)																				✓
39	Khalili-Damghani et al., (2013)												✓								
40	ForouzeshNejad, (2024)												✓				✓				
41	Black et al., (2024)											✓					✓				
42	Klein et al., (2022)							✓													

Table 6
Solution methods used to solve single and multi-objective portfolio project optimization problems

No.	Author's/Year	Metaheuristic Algorithms				Scatter Search	OptTek	Gray–Topsis	DPbQN	Branch-and-Bound	Heuristic	Exact Method	No Model
		GA	TS	PSO	Other								
1	April et al., (2001)		✓		✓	✓	✓					✓	
2	Tselios et al., (2012)										✓		
3	Tselios et al., (2013)										✓		
4	Tselios & Savvas, (2015)	✓	✓										
5	April et al., (2004)		✓		✓	✓	✓					✓	
6	Tselios et al., (2015)	✓	✓										
7	Faezy Razi & Hooman Shariat, (2017)	✓											
8	Wang, (2018)							✓					
9	Shafi et al., (2017)				✓								
10	Relich & Pawlewski, (2017)												✓
11	Mo et al., (2020)												✓
12	Zaidouni et al., (2024)										✓		
13	Tian et al., (2022)	✓											
14	Chen et al., (2024)	✓		✓	✓								
15	Andrade et al., (2021)												✓
16	Costantino et al., (2015)												✓
17	Chen et al., (2024)								✓				
18	Jang, (2019)											✓	
19	Koivisto, (2022)										✓		
20	Elnabwy et al., (2024)										✓		
21	Diaz et al., (2020)										✓		
22	Saiz & Calvet, (2025)	✓											
23	Bai, Wei, et al., (2024)	✓											
24	Nonino, (2017)												✓
25	Bai, An, et al., (2024)	✓											
26	Moon et al., (2023)										✓		
27	Bai, Zhang, et al., (2024)	✓											
28	Riekki & Mämmelä, (2021)												✓
29	Bai et al., (2023)	✓											
30	Soleymani et al., (2024)	✓									✓		
31	Liu, (2022)										✓	✓	
32	Golghamat Raad et al., (2020)				✓								
33	Shafiabady et al., (2023)												✓
34	Agrawal et al., (2025)									✓			
35	Araújo et al., (2023)												✓
36	Cruz-Reyes et al., (2015)	✓										✓	
37	Bai, Liu, et al., (2024)	✓											
38	Saravanan & Sangeetha, (2022)				✓						✓		
39	Khalili-Damghani et al., (2013)	✓									✓		
40	ForouzeshNejad, (2024)										✓		
41	Black et al., (2024)												✓
42	Klein et al., (2022)												✓

Interestingly, several studies in the review adopt no explicit mathematical model, instead focusing on conceptual frameworks or qualitative approaches that demonstrate the feasibility of AI integration into portfolio management. While these contributions lack computational depth, they provide important insights into methodological directions and practical applications. In summary, the classification of solution methods underscores the critical role of metaheuristic algorithms in AI-based project portfolio management while also reflecting the value of hybrid and exact approaches in specific contexts. The diversity of methods illustrates the adaptability of AI techniques, offering portfolio managers a broad toolkit to address the complexity, uncertainty, and strategic trade-offs inherent in multi-project environments.

4.5. Putting all together

The reviewed literature demonstrates a clear evolution in the integration of artificial intelligence with project portfolio management, spanning methodological, contextual, and strategic dimensions. In terms of algorithms, early reliance on traditional neural networks and metaheuristic techniques has gradually expanded to encompass deep learning, reinforcement learning, and hybrid models, reflecting the growing complexity of portfolio problems. Case studies highlight the versatility of these methods across diverse domains from finance, IT, and healthcare to energy, defense, and environmental sustainability

where the portfolio perspective provides structure while AI enhances analytical depth and adaptability. The objectives pursued by scholars have also shifted from narrow financial optimization toward broader goals such as risk reduction, uncertainty management, prioritization, and resource allocation, underscoring AI's capacity to address both efficiency and resilience. Solution methods mirror this trajectory, with metaheuristics dominating but increasingly complemented by heuristic, exact, and hybrid approaches tailored to specific portfolio contexts. Collectively, these findings confirm that the synergy between project portfolio frameworks and AI techniques enables more strategic, adaptive, and intelligent decision-making, offering robust support for organizations managing complex, multi-project environments.

5. Challenges in applying AI techniques and algorithms in the field of PPM problems

While artificial intelligence offers significant opportunities to enhance project portfolio management, its practical application is not without obstacles. The reviewed studies reveal that implementing AI in this domain involves addressing technical, organizational, and ethical concerns that can hinder adoption and limit effectiveness. These challenges stem from issues such as data quality, model transparency, integration with existing systems, and the dynamic nature of portfolio environments. Moreover, organizational readiness, privacy considerations, and the scalability of AI solutions further complicate deployment. Understanding these barriers is essential for developing robust, trustworthy, and sustainable AI-enabled portfolio management frameworks.

- *Data quality, availability and standardization:* Reliable AI-driven portfolio decisions depend critically on rich, consistent, and well-labelled data; however, project repositories are often fragmented, heterogeneous, and missing key attributes (e.g., cost breakdowns, risk logs, or outcome labels), which degrades model training and generalization. In practice, projects span multiple systems (ERP, PM tools, spreadsheets) so consolidating and pre-processing data consumes considerable effort and introduces bias if ad-hoc cleaning rules are applied. Empirical studies in the review illustrate these problems (e.g., large-scale text and record extraction issues in maintenance and trial portfolios), and recommend careful feature engineering, schema harmonization, and provenance tracking before deploying ML or DL models. (Mo et al., 2020; Klein et al., 2022; Liu, 2022).
- *Model interpretability and explainability:* Many high-performance methods used for portfolio tasks (deep nets, ensembles, DRL) behave like black boxes, which creates a trust gap for senior managers who must justify portfolio adjustments to stakeholders; without transparent explanations, model recommendations risk rejection or misapplication. The literature highlights hybrid or neuro-fuzzy approaches and the promise of XAI techniques as partial remedies i.e., combining interpretable surrogates, rule extraction, or fuzzy-based outputs with predictive models to make trade-offs and rationale explicit for governance. Achieving a balance between predictive power and interpretability remains a major, recurrent theme. (Zaidouni et al., 2024; Costantino et al., 2015).
- *Integration with legacy PPM systems and operational workflows:* Embedding AI into existing portfolio pipelines is not only a technical integration task but also an orchestration challenge: legacy PPM tools, decentralized processes, and heterogeneous reporting formats block smooth data flow and automation of recommendations. Case studies show that fixes such as API layers, centralized intake workflows, or semi-automated ETL are necessary but require governance redesign and investment. Consequently, even accurate models may fail to deliver impact unless they are tightly coupled with operational workflows and governance mechanisms. (Black et al., 2024; Elnabwy et al., 2024).
- *Organizational readiness, skills and change resistance:* Successful AI adoption in portfolio management hinges on people as much as on algorithms: insufficient analytical skills, weak executive sponsorship, or cultural resistance to data-driven prioritization impede uptake. Several reviewed studies report that lack of stakeholder training, unclear roles for human–AI decision loops, and low organizational maturity undermine otherwise promising technical pilots. Addressing this challenge requires tailored capacity building, transparent KPIs for AI outcomes, and co-design processes to align models with managerial routines. (Shafiabady et al., 2023; Elnabwy et al., 2024).
- *Modeling interdependencies, uncertainty and dynamic environments:* Project portfolios feature complex interdependencies (resource contention, technical synergies, precedence relations) and operate under stochastic disturbances; naïve models that ignore these relationships produce suboptimal or unstable portfolios. The review shows rising use of RL/DRL, ensemble and hybrid metaheuristic approaches to capture dynamics and inter-project coupling, but properly modeling uncertainty (scenario design, correlated risks) and validating policies across plausible futures remains hard, especially for long-horizon planning. Robustness, scenario fidelity, and mechanisms for safe adaptation are therefore essential research and deployment priorities. (Shafi et al., 2017; Mohagheghi et al., 2019; Micán et al., 2021).
- *Ethical, privacy and cybersecurity concerns:* Project portfolios often include commercially sensitive, personal, or regulated data (R&D plans, health records, contractual terms). Applying AI raises privacy risks (unauthorized inference), ethical dilemmas (bias in prioritization), and attack surfaces (model-poisoning, data exfiltration). The reviewed corpus flags cybersecurity and ethics as non-negligible barriers and recommends privacy-preserving techniques (differential privacy, secure federated learning), bias audits, and clear accountability frameworks as prerequisites for trustworthy PPM automation. (Black et al., 2024).
- *Scalability, maintainability and transferability of models:* Even when a model performs well in a pilot, scaling to enterprise portfolios uncovers computational costs, model drift, and transferability limits across domains. Training complex hybrids (GA-BPNN, DRL agents, LLM-assisted heuristics) can be costly and sensitive to hyperparameters; models also need ongoing retraining and monitoring as portfolios and external contexts evolve. The literature points

to transfer learning, modular architectures, lightweight surrogate models, and automated retraining/monitoring pipelines as practical mitigations but establishing industry benchmarks and reproducible evaluation protocols remains an open need. (Tian et al., 2022; Soleymani et al., 2024; Saiz & Calvet, 2025).

The literature review highlights that, despite the rapid progress of artificial intelligence techniques in project portfolio management, a number of recurring challenges remain. These difficulties are not only technical but also organizational and contextual, affecting the reliability, acceptance, and sustainability of AI-driven solutions. To provide a structured view, the key challenges and their corresponding mitigation strategies are summarized in the following table.

Table 7
Summary of Challenges in Applying AI to PPM

Challenge	Proposed Solutions	References
Data quality, availability and standardization	Data harmonization, feature engineering, provenance tracking	Mo et al. (2020); Klein et al. (2022); Liu (2022)
Model interpretability and explainability	Use of XAI methods, fuzzy/neuro-fuzzy hybrids, surrogate models	Zaidouni et al. (2024); Costantino et al. (2015)
Integration with legacy PPM systems	API integration layers, ETL automation, governance redesign	Black et al. (2024); Elnabwy et al. (2024)
Organizational readiness and resistance	Capacity building, stakeholder training, human–AI co-design	Shafiabady et al. (2023); Elnabwy et al. (2024)
Modeling interdependencies and uncertainty	Hybrid metaheuristics, RL/DRL, scenario-based robustness validation	Shafi et al. (2017); Mohagheghi et al. (2019); Micán et al. (2021)
Ethical, privacy and cybersecurity concerns	Privacy-preserving learning, bias audits, accountability frameworks	Black et al. (2024)
Scalability, maintainability and transferability	Transfer learning, modular architectures, surrogate models, automated monitoring	Tian et al. (2022); Soleymani et al. (2024); Saiz & Calvet (2025)

Overall, the classification confirms that overcoming these barriers requires a balanced combination of methodological innovation, organizational adaptation, and ethical safeguards. Addressing data quality, interpretability, system integration, and scalability alongside issues of trust and governance is critical for enabling robust adoption. By acknowledging these challenges and potential solutions, researchers and practitioners can pave the way for more effective and sustainable use of AI in project portfolio management.

6. Future direction

Drawing from the analysis of the four central dimensions AI methods and algorithms, case studies, research objectives, and solution approach this review identifies several promising directions for future exploration. These directions point toward significant opportunities to advance both the theoretical foundations and the practical applications of artificial intelligence in the field of project portfolio management.

Advancements in AI Methods and Algorithms: Future investigations should move beyond the current reliance on traditional neural networks and metaheuristic approaches to embrace more sophisticated and adaptive paradigms. Techniques such as deep reinforcement learning, transfer learning, and large language models hold considerable potential for managing the inherent complexity, uncertainty, and dynamic nature of modern project portfolios. At the same time, hybrid and ensemble systems that combine the strengths of multiple techniques are likely to become increasingly important. Such approaches can help achieve an optimal balance between predictive accuracy, interpretability of outcomes, and computational efficiency, ensuring that AI-driven models remain both effective and practical in diverse organizational contexts.

Broadening the Scope of Case Studies: A majority of the documented applications of AI in PPM are concentrated in familiar areas such as finance, information technology, and a few industrial sectors. To strengthen the field, future studies should actively explore underrepresented and emerging domains. Examples include smart city development, climate resilience initiatives, infrastructure modernization, and digital transformation projects. Conducting in-depth case studies within these new contexts would not only validate the generalizability of AI-based methods but also highlight domain-specific constraints, opportunities, and success factors that may currently be overlooked. Such diversity in applications will expand the evidence base and improve the relevance of research findings for decision-makers across multiple sectors.

Expanding Objectives and Decision Criteria: To date, most research has emphasized narrow objectives, particularly financial returns and risk minimization. However, the evolving landscape of project management requires a broader and more holistic set of evaluation criteria. Future work should integrate additional dimensions such as environmental sustainability, stakeholder engagement, social responsibility, and long-term adaptability of portfolios. AI models can be designed to function within multi-criteria decision-making frameworks that account for both tangible and intangible measures of success. This shift will enable organizations to align portfolio strategies with broader societal and environmental goals, meeting the growing global demand for more ethical, sustainable, and inclusive approaches to governance.

Enhancing and Diversifying Solution Methods: Although metaheuristic optimization techniques have dominated the literature, there is considerable scope for developing more advanced and diversified solutions. Hybrid methods that integrate heuristics, exact optimization techniques, and machine learning models can deliver more robust and adaptable results. Furthermore, incorporating explainable AI and interpretable optimization methods will be essential for building managerial trust and encouraging wider adoption of computational tools in practice. Future research should also prioritize the creation of scalable, automated, and continuously adaptive systems capable of real-time learning and monitoring. Such pipelines will help organizations ensure that AI-based solutions remain reliable and relevant in dynamic portfolio environments where conditions and priorities can change rapidly. Fig. 6 shows a summary of suggestions for future research.

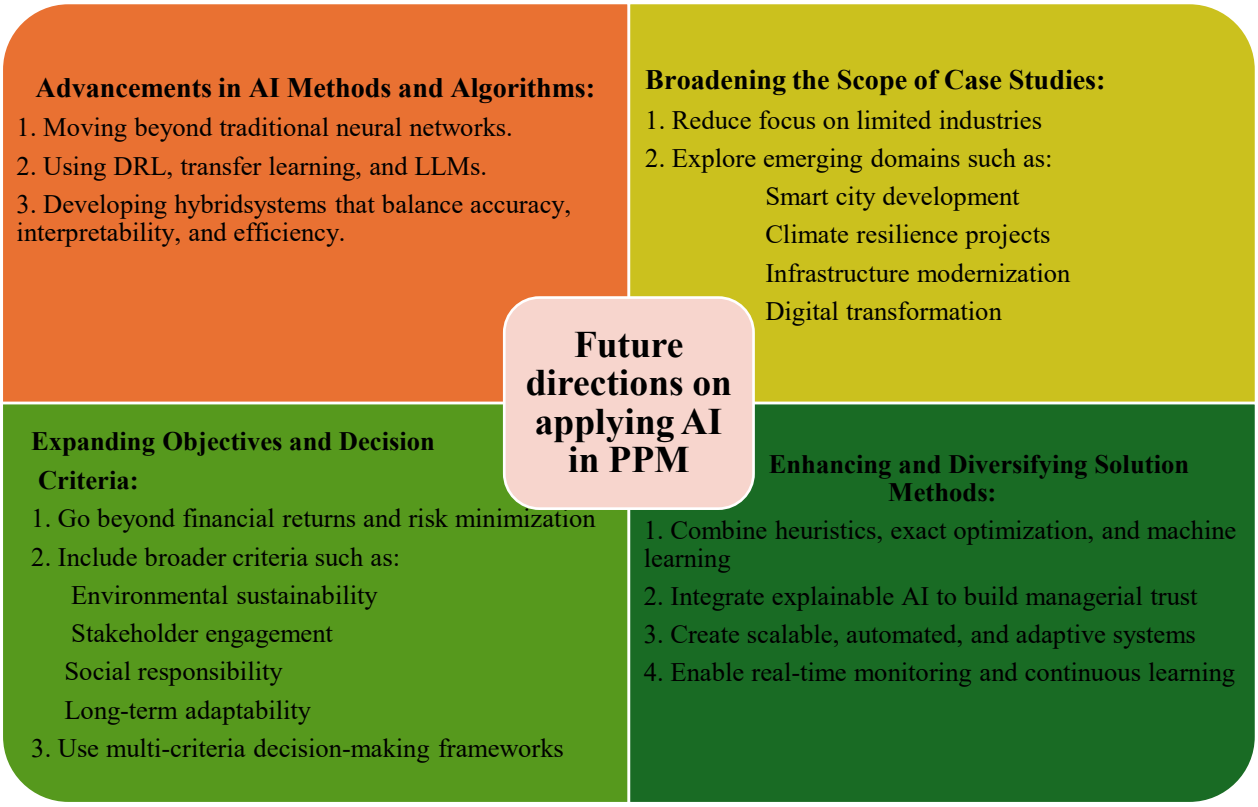

Fig. 6. A summary of future research directions for applying AI techniques and algorithms in PPM.

In conclusion, advancing research in these four areas requires more than just technical innovation. It also calls for a deliberate focus on applicability, adaptability, and acceptance across a range of organizational settings. By simultaneously improving algorithms, expanding case studies, broadening decision criteria, and diversifying solution methods, the integration of AI into project portfolio management can evolve into a powerful tool for delivering more strategic, sustainable, and impactful decision support in the years ahead.

7. Conclusions

In this paper, we attempted to provide a comprehensive review of the application of AI in the field of project portfolio management. Our review showed that AI has become a transformative force in the field of PPM, transforming traditional approaches to project selection, prioritization, risk management, and resource allocation. A wide range of AI techniques, including machine learning, neural networks, reinforcement learning, data mining, fuzzy systems, and evolutionary algorithms, have been applied to improve forecast accuracy, optimize project portfolio configurations, and enable dynamic adjustments under uncertainty. Among these, machine learning models such as decision trees, support vector machines, and ensemble classifiers have been frequently employed to predict project success and classify risks, while neural networks and their variants (ANN, RNN, BP, and LSTM) have been very effective in predicting project performance and evaluating project portfolio benefits. Genetic algorithms and other metaheuristic approaches, often combined with neural networks, further improve project portfolio optimization, especially in single-objective and multi-objective problems where a trade-off between cost, risk, and value must be made.

Hybrid approaches are increasingly visible in the literature, and many studies integrate AI techniques with classical decision-making models or multi-criteria frameworks. These hybrids take advantage of the computational power of AI while maintaining the interpretability and structure of traditional methods, making them particularly effective in complex and uncertain environments. For example, reinforcement learning and fuzzy logic have been adopted to support adaptive portfolio optimization and risk assessment, respectively, highlighting the power of AI in managing uncertainty and dynamic constraints.

Additionally, emerging methodologies such as NLP and LLMs are expanding the scope of analytics by enabling automated extraction of insights from unstructured project documents and stakeholder communications.

The reported benefits of integrating AI into PPM are significant. In industries ranging from IT and construction to defense and energy, AI-based tools have increased forecast accuracy, improved resource allocation efficiency, reduced risks, and enabled data-driven decision making. By shifting from reactive to proactive portfolio management, AI is enabling organizations to more effectively align project investments with strategic objectives, optimize the use of scarce resources, and respond quickly to external changes. In addition, AI-based dashboards and decision support systems provide real-time recommendations and increase transparency and managerial confidence in portfolio-level decisions.

Despite these advances, adoption is not without challenges. Technical barriers include the interpretability of complex AI models and their integration with existing PPM platforms. Organizational and cultural challenges stem from limited managerial expertise in AI, resistance to change, and concerns about workforce turnover. Data quality, availability, and privacy also remain critical bottlenecks: without reliable and comprehensive datasets, AI models risk producing biased or misleading results. These barriers limit the scalability and reliability of AI applications in real-world PPM contexts.

This review also highlights several research gaps. First, while many studies focus on predictive modeling and optimization, less attention has been paid to the longitudinal validation of AI systems in practice. Second, hybrid approaches, while promising, need to be explored more systematically to develop frameworks for integrating AI with human judgment and governance structures. Third, the ethical and privacy implications of using sensitive project data for AI-based decision-making have been less explored. Finally, the application of AI-enhanced metaheuristic algorithms to single-objective and multi-objective optimization problems provides a good foundation for future research, particularly in balancing financial, strategic, and sustainability considerations in project portfolios. As a result, AI holds the promise of transforming project portfolio management into a more adaptive, intelligent, and value-driven discipline. By effectively utilizing AI techniques whether individually or in combined configurations organizations can not only improve efficiency and accuracy, but also strengthen resilience to uncertainty and risk. However, realizing the full potential of AI in project portfolio management requires addressing technical and organizational challenges, ensuring high-quality, ethically managed data, and expanding research into integrated and scalable models. Future work should continue to explore the synergies between AI tools and meta-heuristic optimization, moving towards robust decision support systems capable of managing project ecosystems of increasing complexity.

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