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# **Artificial Intelligence in Project Scheduling Management**

A Systematic Literature Review

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**ABSTRACT:**

The integration of artificial intelligence into project management practices represents one of the most significant technological transformations in contemporary scheduling methodologies. As projects grow increasingly complex and face greater environmental uncertainty, traditional scheduling approaches often prove inadequate. This systematic literature review examines how AI applications are reshaping project scheduling management, investigating which techniques are being employed and their measurable impact on scheduling effectiveness across diverse project environments. We implemented a rigorous systematic review methodology following Fink's seven-step model, incorporating an innovative triangulated screening approach that combined manual evaluation with AI-assisted validation techniques. Through comprehensive quality assessment and methodological evaluation of initially identified 195 articles, 66 studies published between 2015-2024 were ultimately selected for in-depth analysis.

Our analysis identified 10 distinct AI fields, Evolutionary Algorithms, Neural Networks, Swarm Intelligence, Optimization and Metaheuristics, Classical Machine Learning Models, Fuzzy Systems, Reinforcement Learning, Agent-Based Systems, Generative Pre-trained Transformers, and Knowledge Representation and Reasoning, comprising 70 unique techniques applied across 9 core project scheduling functions, including Resource Management, Constraint-Based Scheduling, Time Estimation and Duration Prediction, Task Scheduling and Sequencing, Multi-Objective Scheduling, Uncertainty Management and Stochastic Scheduling, Dynamic and Real-Time Scheduling, Critical Path Identification, and Schedule Optimization. Evolutionary Algorithms, particularly Genetic Algorithms, demonstrated pronounced dominance, while hybrid-method implementations consistently outperformed single-method approaches across key performance metrics. Moreover, the construction industry showed a substantial majority (62%) of applications, raising important questions about cross-sector generalizability of current research findings.

This review contributes theoretically through a novel taxonomic framework for classifying AI applications in project scheduling contexts and identification of divergent adoption trajectories between established and emerging methodologies. From a practical perspective, our implementation maturity assessment revealed concerning gaps, with only one-third of studies reaching experimental validation with real-world data. This maturity limitation suggests practitioners should approach technique selection contextually rather than implementing trending approaches without consideration of their specific scheduling challenges and organizational readiness. Looking forward, the field would benefit substantially from development of standardized frameworks that effectively transition theoretical models into operational implementations and from comparative analyses across diverse sectors, enhancing understanding of industry-specific scheduling constraints and their influence on optimal AI technique selection.

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**KEYWORDS:** Artificial Intelligence, Project Management, Scheduling, Sequencing, Review, Algorithms, Neural Networks, Resource Optimization, Uncertainty, Optimization, Management

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## 1. Introduction

This chapter provides a comprehensive overview of the study, including the background of project scheduling management and artificial intelligence and the research problem of the study. It also highlights the identified research objectives and questions related to exploring the role of various AI techniques in enhancing project scheduling effectiveness across different industries and project types. Lastly, it describes the structure of the thesis, outlining the systematic literature review methodology and subsequent analysis that forms the foundation of this research.

Project scheduling represents one of the foundational pillars of effective project management, serving as the temporal framework through which project activities are coordinated and executed. As Miranda & Helia (2019) emphasize, scheduling becomes a basic requirement for project management related planning and analysis when projects do not proceed according to initial plans. In its most fundamental form, scheduling constitutes the process of determining the commencement and completion dates for various tasks and activities throughout the product development process (Zhang, 2024).

The significance of effective project scheduling cannot be overstated within contemporary project management practice. Herroelen (2004) highlights that scheduling has been the subject of intensive research since the late 1950s due to its obvious practical importance. This historical research emphasis reflects scheduling's critical role in project success, as it directly influences resource utilization, timeline adherence, and budget management. This importance manifests in the prevention of project escalation, as inadequate planning and control are frequently identified as major variables distinguishing between escalated and non-escalated projects (Herroelen, 2004). Underscoring this criticality with empirical evidence, Mostafa & Alsalman (2021) quantify this significance, noting that 40% of project failures stem from poor planning and misuse of human resources. Research indicates that organizations investing in advanced project management tools and scheduling methodologies experience substantial reductions in runaway projects, demonstrating clear returns on such technological investments (Herroelen, 2004).

Despite their established importance, traditional scheduling methodologies face significant limitations in contemporary project environments. Current non-AI scheduling approaches frequently rely on manual processes and subjective decision-making that produce inefficiencies, delays, and suboptimal resource allocations, ultimately undermining project performance (Egbedion, 2024). These limitations have become increasingly problematic as projects grow in complexity and face greater uncertainty.

Artificial Intelligence (AI) has emerged as a transformative force in the global economy, with Bughin et al. (2018) projecting its potential contribution to reach \$13 trillion by 2030, equivalent to a 1.2% annual boost in global GDP. Despite this promise and AI's potential to disrupt the way organizations operate; significant challenges are faced by organizations trying to harness AI's capabilities. A 2019 Gartner survey reveals that 37% of enterprises remain in the exploratory phase of AI strategy development, while 35% struggle to identify viable applications (Gartner, 2019). This gap underscores the potential for industries that adopt AI-driven innovations to remain competitive. In a quote from Chris Howard, distinguished research vice president at Gartner, he highlighted the growing importance of utilizing AI tools to revamp existing work practices:

*"If you are a CIO and your organization doesn't use AI, chances are high that your competitors do, and this should be a concern."*

The imperative to integrate AI into organizational frameworks is thus not merely a technological consideration but about redefining workflows, decision-making, and strategic resilience in an increasingly dynamic global landscape.

However, emerging evidence suggests AI holds transformative potential in managing project scheduling. Weiser & von Krogh (2023) mentions that AI enables organizations to navigate deep uncertainty by facilitating rapid experimentation cycles, allowing decision-makers to test hypotheses and adapt strategies dynamically. The authors further emphasize AI's role in agenda-setting by continuously scanning internal and external environments, AI systems help stakeholders identify emerging risks and prioritize critical issues before they escalate. Beyond prioritization, the authors also mentioned how AI enhances problem-solving in high-stakes scenarios. Additionally, the authors highlight (generative) AI's combinatorial abilities, which allow it to synthesize

disparate information and generate innovative alternatives that traditional analysis might overlook.

Recognizing these advantages, organizations are increasingly adopting AI solutions to enhance efficiency in project delivery and management processes (Egbedion, 2024). Empirical research demonstrates the tangible benefits of this transition, as AI-enabled projects consistently demonstrate superior performance in scheduling accuracy, resource utilization efficiency, adherence to timelines, and overall cost-effectiveness when compared to projects using conventional scheduling approaches (Egbedion, 2024).

Despite the growing adoption of AI in project scheduling, there remains a significant gap in understanding which specific AI techniques are most effective for different scheduling challenges and project contexts. While numerous studies have explored individual AI applications in specific project scenarios, a comprehensive synthesis of this knowledge is lacking. This systematic literature review addresses this gap by analyzing the range of AI techniques being applied to project scheduling challenges across diverse industries and project environments.

To explore which AI techniques are utilized in project scheduling and the impact of those technologies on project scheduling performance, two research questions were formulated:

What "artificial intelligence applications" are being used for "project scheduling" in "project management"?

How does "artificial intelligence" impact "project scheduling" in "project management"?

This research employs a systematic literature review methodology to comprehensively identify, evaluate, and synthesize existing knowledge on AI applications in project scheduling. The methodology ensures rigorous coverage of relevant literature through structured search strategies, clear inclusion and exclusion criteria, and thorough quality assessment of selected studies.

This thesis unfolds across five chapters to address the research questions comprehensively. The current chapter introduces the research context, highlights the significance of project scheduling and AI integration, and establishes the key research questions. Chapter 2 lays the conceptual groundwork by exploring relevant project scheduling

approaches and AI techniques, helping readers understand these intersecting domains. Chapter 3 outlines the systematic literature review methodology, detailing the search strategy, selection criteria, and analytical approach adopted. Chapter 4, then presents a synthesis of findings from the selected papers, mapping various AI fields and their specific techniques with their impacts across project scheduling functions and industry contexts. The thesis concludes with Chapter 5, where we discuss theoretical and practical implications, acknowledge limitations, and suggest promising directions for future research in this rapidly evolving field.

## **2. Theoretical Background**

This section establishes the knowledge foundation needed for studying artificial intelligence applications in project scheduling through careful review of key literature. The theoretical framework first outlines established project scheduling methods, functions, and performance metrics used in traditional project management, followed by an exploration of artificial intelligence types, techniques, and development paths. By examining these areas separately before considering their integration, this section provides the clear terminology and concepts required for the deeper systematic literature review in chapter 4 and 6, which will analyse how these fields come together and evaluate applications of artificial intelligence in project scheduling. This approach ensures proper understanding of core concepts before exploring their practical combination in modern project environments.

### **2.1 Project Scheduling in Project Management**

More technically, Herroelen (2004) defines scheduling as the optimal allocation of scarce resources to activities over time, particularly focusing on project activities subject to precedence and resource constraints. The allocation decisions Herroelen describes inherently depend on accurate duration estimates, establishing time estimation and duration prediction as essential scheduling functions that determine the temporal boundaries within which all other scheduling decisions operate. This conceptualization of scheduling is formalized through established methodological frameworks in the project management discipline. The Project Management Body of Knowledge (PMBOK) establishes a structured approach to scheduling that encompasses six major processes: plan schedule management, define activities, sequence activities, estimate activity durations, develop schedule, and control schedule (Miranda & Helia, 2019). Within these processes, time estimation and duration prediction emerge as crucial components that enhance project control and informed decision-making. Building on these foundational processes, specialized approaches have emerged for different project contexts. For instance, the Software Project Scheduling Problem (SPSP) represents a specific manifestation of these principles, wherein project managers assign tasks to employees while considering task

precedence and dependencies to ensure project completion (Mostafa & Alsalman, 2021). Zhang (2024) further emphasizes that effective scheduling ensures appropriate resource allocation, risk minimization, and achievement of key milestones, all essential elements for project success in competitive business environments.

### **2.1.1 Core Project Scheduling Methodologies and Functions**

Having established the fundamental importance of project scheduling, attention must be directed to the specific techniques and approaches employed in scheduling practice.

#### **Task Sequencing and Network Analysis Techniques**

While theoretical frameworks provide conceptual foundations for scheduling, specific methodological techniques enable practical implementation. The arrangement of activities in logical sequences forms the backbone of project planning, making task sequencing a foundational function within scheduling that enables both temporal organization and resource coordination across the entire project lifecycle. Among these, the Critical Path Method (CPM) remains one of the most widely applied scheduling techniques in contemporary project management. Firdaus & Pulansari (2023) highlight that CPM identifies critical tasks directly impacting project duration, enabling project managers to prioritize these activities to avoid delays. Building on this functional understanding, Hein Soe & Min Htike (2018) elaborate that CPM utilizes a network diagram to represent project activities and their dependencies, calculating the earliest and latest start and finish times for each activity to identify the critical path. This visibility highlights why critical path identification stands as a fundamental function of project scheduling, creating the essential framework that determines minimum project duration and guides prioritization of critical activities. Critical path identification thus forms the foundation upon which many other scheduling approaches are built.

The directionality of scheduling processes represents another important dimension in project management practice. Project scheduling incorporates both forward and backward scheduling approaches to optimize sequence and timing decisions. Deng et al. (2009) & Lucko et al. (2007) explain that forward scheduling involves planning tasks to start as early as possible, considering their dependencies and resource constraints.

Elaborating on implementation contexts, Lucko et al. (2007) add that forward scheduling is commonly used in the Critical Path Method, where activities are scheduled at the earliest possible time while obeying dependency conditions, helping identify earliest start and finish times for each task and determining the project's minimum duration. These authors further note that forward scheduling helps quickly identify potential bottlenecks and resource constraints early in the project timeline, allowing for proactive adjustments (Lucko et al., 2007).

Complementing forward scheduling with an alternative approach, Deng et al. (2009) and Lucko et al. (2007) contrast this with backward scheduling, which plans tasks to start as late as possible without delaying project completion. Explaining the technical implementation, Deng et al. (2009) and Lucko et al. (2007) explain that backward scheduling in CPM examines the latest possible start and finish times for each activity without impacting the project's end date, proving useful for identifying latest permissible start times and calculating float or slack time for each task. Highlighting the practical benefits, Deng et al. (2009) emphasize that backward scheduling helps optimize resource utilization by delaying tasks to avoid idle time, benefiting scenarios with limited or fluctuating resource availability.

Rather than treating these approaches as mutually exclusive, contemporary scheduling techniques frequently integrate both perspectives. Advanced scheduling techniques often combine forward and backward approaches to capture the advantages of each. Gu et al. (2013) and Yongyi Shou (2007) note that techniques like forward-backward improvement of heuristic and dual ant colony algorithms use both methods to enhance resource allocation and minimize project duration, leading to faster convergence to optimal solutions and better handling of resource constraints and dependencies. This integration exemplifies the evolution toward more sophisticated scheduling approaches that can address the complex, multi-dimensional challenges of modern project environments. Beyond CPM and its extensions, several other established methodologies address specialized scheduling challenges. Program Evaluation and Review Technique (PERT) offers another established approach to project scheduling that specifically addresses duration uncertainty. Putra et al. (2024) explain that PERT calculates expected durations for

project tasks, helping identify critical activities that could delay project completion, with demonstrated potential to reduce project completion times significantly, as evidenced by a case where a project completed in 115 days instead of the planned 133 days. This probabilistic approach enhances schedule reliability in environments with significant variability in activity durations.

Complementing PERT with enhanced capabilities for complex project environments, the Graphical Evaluation and Review Technique (GERT) provides advanced modeling functionality. Pregina & Kannan (2024) highlight that GERT allows for modeling projects with repetitive tasks and multiple outcomes, incorporating feedback loops and multiple sink nodes to analyze various scenarios and their impacts on project timelines, proving particularly valuable for projects with high complexity and stochastic elements that must address issues like false starts and activity repetition. These capabilities make GERT especially suitable for research and development projects where activity paths may branch depending on intermediate outcomes.

For projects with complex interdependencies between components and activities, matrix-based methods offer distinct advantages. The Design Structure Matrix (DSM) represents another versatile scheduling tool that visualizes and manages these interdependencies. Browning (2001) describes DSM as offering visual representation of complex systems and their interdependencies, facilitating management of component relationships, team interactions, information flow among activities, and design parameter relationships. Demonstrating DSM's practical utility in specific industry contexts, Ma et al. (2021) demonstrate that DSM can model rework relationships and mitigate uncertainties in construction project scheduling, generating schedules with improved on-time completion rates and better adaptability to rework scenarios when combined with methods like critical chain project management and max-plus algorithms. This visualization capability proves particularly valuable for concurrent engineering applications where understanding information flow dependencies directly impacts schedule optimization. While these network analysis techniques primarily address activity sequencing and timing, they must be complemented by approaches that explicitly manage resource constraints.

## **Resource Allocation and Optimization Methods**

The Resource-Constrained Project Scheduling Problem (RCPSP) represents a foundational framework within project scheduling research and practice. The prominence of this framework in scheduling literature reflects the central role of resource management as a core scheduling function that bridges abstract planning and concrete execution by matching available capabilities with task requirements. Odedairo & Oladokun (2011) characterize RCPSP as a complex optimization challenge involving the assignment of activities to limited resources while meeting predefined objectives. Elaborating on this characterization, Vanhoucke & Debels (2008) add that RCPSP typically aims to minimize project makespan while accounting for precedence relationships and resource constraints. These constraints manifest in several forms, with Chand et al. (2016) identifying precedence constraints as dependencies between activities where one activity cannot commence until another has finished. Complementing this understanding, Osz & Hegyháti (2018) describe resource constraints as limitations on the availability of resources required by activities, which may be renewable (e.g., manpower, machinery) and must be allocated efficiently to avoid delays. The pervasive nature of these constraints across project environments establishes constraint-based scheduling as a fundamental function that transforms idealistic plans into feasible schedules by systematically incorporating temporal, resource, and technical limitations. Beyond basic resource allocation, effective scheduling requires addressing the distribution of workload across project resources. Workload balancing constitutes another critical dimension of effective project scheduling. Ouazene et al. (2014) define workload balancing as minimizing imbalances between overloaded and underutilized resources. To achieve this balance, various approaches have been developed and implemented in scheduling practice. These approaches include mathematical programming methods (Ouazene et al., 2014) and heuristic algorithms (Farkas et al., 1999). Expanding on the practical benefits of these approaches, Farkas et al. (1999) emphasize that workload balancing improves capacity utilization, reduces delays, and enhances overall system performance, particularly when accounting for task types, machine capabilities, and employee skills.

While the previously discussed methods focus primarily on timing and sequencing, resource management requires specialized scheduling techniques. Resource leveling constitutes an important scheduling technique aimed at optimizing resource allocation over time by smoothing utilization patterns. Damci et al. (2013) define resource leveling as minimizing fluctuations in resource usage without changing project completion time. Expanding on this definition with implementation details, Cheng et al. (2017) add that it involves smoothing resource profiles to avoid sudden spikes or idle periods, leading to more efficient resource management and cost savings. The technical implementation of resource leveling has evolved to incorporate advanced computational approaches. Various approaches support resource leveling, including fuzzy clustering chaotic-based differential evolution (Cheng et al., 2017) and genetic algorithms (Damci et al., 2013). Highlighting the practical benefits that motivate these techniques, Tran & Hoang (2014) emphasize that resource leveling aims to achieve smoother resource utilization, minimize logistical problems, and prevent delays and cost overruns caused by inefficient resource management. These benefits are particularly apparent in construction projects where labor and equipment resources must be coordinated across multiple project phases. However, even the most optimized resource allocation plans must address another fundamental challenge in project scheduling: the inherent uncertainty of real-world project environments.

### **Schedule Uncertainty Management Approaches**

The presence of uncertainty within project environments creates distinct challenges for scheduling methodologies. Uncertainty management represents a significant challenge that project scheduling methodologies must address through specialized approaches. Lambrechts et al. (2006) characterize stochastic scheduling as addressing uncertainty in activity durations and resource availability through developing robust schedules that can adapt to unforeseen events. The ubiquitous nature of uncertainty in real-world projects establishes uncertainty management as a fundamental scheduling function that transforms idealistic deterministic plans into practical, resilient schedules capable of withstanding variability. Their research indicates that both proactive and reactive strategies combine a-priori sequencing decisions with dynamic execution to manage this

uncertainty. Providing further context to uncertainty management in scheduling, Oberemok & Oberemok (2018) note that stochastic project management features decisions and actions described by stochastic functions, reflecting the inherent uncertainty in project execution.

Despite its enduring utility, CPM has limitations in addressing resource constraints and uncertainty management. Addressing these limitations, CPM has been enhanced through complementary methodologies such as Critical Chain Buffer Management (CCPM). Firdaus & Pulansari (2023) demonstrate that CCPM introduces buffers to protect project timelines from uncertainties, reducing a project's overall duration to 145.3 days compared to 164 days with CPM alone. Supporting this finding with additional evidence, Anastasiu et al. (2023) observe that integrating both methods leads to significant time savings, with CCPM introducing project, feeding, and resource buffers to mitigate delays, resulting in a construction project saving 36 days compared to CPM. Examining the specific mechanisms through which CCPM enhances scheduling, Xiao & Chu (2022) and Gomez & Guillamón (2025) explain that CCPM introduces project buffers and feeding buffers to absorb delays and protect the critical chain from disruptions. Xiao & Chu (2022) further elaborate on implementation practices, noting that buffers are dynamically monitored with warning points set to trigger corrective actions when necessary. Expanding on CCPM's resource management capabilities, Gomez & Guillamón (2025) add that CCPM considers resource availability and prioritizes tasks to ensure efficient resource utilization. Raz et al. (2004) describe CCPM's fundamental approach as shortening task duration estimates and reallocating safety time into buffers, which are monitored to manage project progress. As a result, we can observe that approaches like CCPM enable projects to adapt to changing conditions while maintaining focus on critical deliverables and timelines.

The management of uncertainty presents particular challenges in scheduling that require specialized approaches. Dependent-Chance Programming (DCP) offers a specialized approach to uncertainty management in project scheduling that addresses the probabilistic nature of many scheduling parameters. Odedairo & Oladokun (2011) describe DCP as a method addressing uncertainty in project scheduling problems,

considering multiple objectives and constraints simultaneously, including resource limitations and activity dependencies. Highlighting its relevance to practical scheduling challenges, Davari & Demeulemeester (2016) emphasize that DCP is particularly relevant to project scheduling as it enables more realistic modeling of real-world uncertainties and supports informed decision-making in complex project environments. This approach explicitly incorporates uncertainty into scheduling models rather than simplifying with deterministic assumptions.

Simulation approaches provide another important technique for managing scheduling uncertainty through scenario analysis. Monte Carlo simulation represents another important technique for managing uncertainty in project scheduling through statistical sampling and analysis. Nazaruddin et al. (2024) characterize Monte Carlo simulation as a widely used technique for modeling and analyzing systems with risks and uncertainties. Explaining its implementation methodology, Fadjar et al. (2022) explain that it involves conducting experiments on probabilistic elements through random sampling to estimate project duration and completion probabilities. Highlighting its practical management benefits, Sharma (2019) emphasizes that Monte Carlo simulation helps project managers plan more realistic schedules by quantifying risk and uncertainty effects, enabling better justification and communication when confronting unreasonable project expectations. This approach is particularly valuable in complex projects where the interaction of multiple uncertainties cannot be predicted through simpler analytical methods. Beyond managing uncertainty, modern project scheduling must also balance multiple competing objectives simultaneously.

### **Multi-Objective and Dynamic Scheduling**

As project management has evolved to address increasingly complex environments, scheduling approaches have similarly advanced to accommodate multiple objectives and dynamic conditions. Modern scheduling approaches increasingly acknowledge multiple competing objectives that must be simultaneously optimized. Senouci et al. (2019) observe that multi-objective scheduling in project management involves optimizing conflicting objectives such as minimizing project duration, cost, and environmental impact. The inherent tension between competing objectives in modern projects positions multi-

objective scheduling as a core function that distinguishes sophisticated project management from simplistic time-focused approaches, enabling balanced optimization across various stakeholder requirements. This complexity necessitates sophisticated optimization techniques to effectively balance competing goals. Similarly, scheduling must adapt to dynamic project environments where conditions frequently change during execution. Odedairo & Alarjani (2024) describe dynamic or real-time scheduling as adapting schedules to respond to uncertainties and changes during project execution, encompassing baseline scheduling, risk analysis, and project control. The increasing frequency of disruptions in contemporary project environments elevates dynamic scheduling from merely a reactive technique to a core scheduling function that ensures project viability through continuous adjustment rather than periodic replanning. Building on this understanding, we analyze another paper by Fahmy et al. (2019) where he adds that dynamic scheduling utilizes multi-objective optimization of cost, time, resources, and cash flow for resource optimization under uncertainty.

Closely related to this adaptive and optimization-driven perspective is the economic dimension of scheduling, where trade-offs between project duration and financial cost become central. Time-cost trade-off analysis represents another critical dimension of project scheduling that directly addresses economic efficiency. V. Agarwal et al. (2013) explain that project scheduling involves decisions regarding time and cost for each activity, with the set of decisions resulting in desirable time-cost realization constituting the time-cost trade-off problem. Emphasizing its practical significance, these authors emphasize the economic importance of optimizing the balance between time and cost in project completion (V. Agarwal et al., 2013). Providing greater technical precision, the same researchers note that in time-cost trade-off problems, the objective is determining each activity's duration to achieve minimum total direct and indirect project costs (V. Agarwal et al., 2013). Defining the cost components that must be considered in this analysis, V. Agarwal et al. (2013) further clarify that direct costs include materials, human resources, and equipment, while indirect costs encompass lease holds, machinery hiring, and management operations. This comprehensive view of costs enables more informed scheduling decisions that balance temporal and financial objectives.

For scheduling problems with complex mathematical structures, optimization techniques provide rigorous solution approaches. Mixed Integer Linear Programming (MILP) provides a mathematical optimization approach to project scheduling that leverages operations research techniques for schedule optimization. Cajzek & Klanšek (2016) note that MILP is used for optimal project scheduling, especially under nonconvex time-cost relations resulting from alternative technological processes or resource availability, involving formulation of scheduling problems as mathematical models with integer and linear constraints to optimize complex, combinatorial scheduling challenges. This approach enables exact solutions for scheduling problems of moderate complexity and provides the foundation for heuristic approaches to larger problems. The persistent gap between initial scheduling solutions and theoretically optimal schedules establishes schedule optimization as a fundamental scheduling function that systematically refines preliminary plans to enhance performance across multiple dimensions including time, cost, and resource utilization. While these optimization techniques enhance schedule development, effective project management also requires robust frameworks for monitoring and controlling schedule performance during execution.

### **Schedule Performance Measurement and Control**

Beyond technique-specific approaches, integrated methodologies offer comprehensive frameworks for project schedule management and evaluation. Earned Value Management (EVM) provides a structured methodology for integrating project performance measurement across multiple dimensions. Lavanya et al. (2018), Rodriguez et al. (2017), and Vandevoorde & Vanhoucke (2006) describe EVM as a project management methodology that integrates scope, schedule, and cost to assess project performance and progress, combining these critical elements to provide a comprehensive view of project status and enabling calculation of cost and schedule variances, performance indices, and forecasts. Emphasizing EVM's practical utility, Lavanya et al. (2018) note that EVM is widely applied across various industries and provides early warnings of potential cost overruns and schedule delays. This early warning capability enables proactive management interventions before problems escalate.

To operationalize EVM for schedule management, specific metrics provide standardized measurement approaches. Within the EVM framework, the Schedule Performance Index (SPI) serves as a key metric for evaluating temporal performance. Kim (2009) & Olano et al. (2009) define SPI as measuring the efficiency of time utilization, calculated by dividing Earned Value (EV) by Planned Value (PV), with values of 1.0 indicating on-schedule performance, greater than 1.0 indicating ahead-of-schedule performance, and less than 1.0 indicating behind-schedule performance. Highlighting SPI's management significance, Kim (2009) emphasizes that SPI is crucial for project managers to assess schedule performance and make necessary adjustments to maintain project timeline adherence. This standardized approach provides clear thresholds for intervention decisions based on quantitative performance data.

While SPI provides critical insights into current performance, forward-looking metrics enhance predictive capabilities. The To Complete Schedule Performance Indicator (TCSPI) extends schedule performance measurement with future-oriented insights essential for proactive management. Beck & Kovacs (2018) define TCSPI as a metric forecasting the efficiency required to complete remaining work within the planned schedule, calculated by dividing the remaining work (total planned work minus earned work) by the remaining time (total planned time minus elapsed time), helping project managers understand the performance level needed to meet deadlines and proving particularly valuable when projects fall behind schedule. This predictive capability transforms schedule management from reactive to proactive by identifying potential problems before they manifest. These measurement approaches collectively create a comprehensive framework for schedule monitoring and control. Kim (2009) observes that EVM provides a comprehensive framework for tracking project performance by comparing planned progress with actual progress and the value of work performed. Adding further detail on implementation, the same author notes that SPI measures current schedule performance and identifies deviations from the planned schedule (Kim, 2009). Elaborating on SPI's analytical benefits, Kim (2009) and Olano et al. (2009) emphasize that SPI help quantify the degree of schedule variance, enabling more precise management responses. Complementing these insights with forward-looking information, Beck & Kovacs (2018) highlight that

TCSPI predicts future schedule performance required for on-time completion, providing a forward-looking perspective that enables preventive interventions rather than corrective actions.

### **2.1.2 Metrics for Evaluating Scheduling Effectiveness**

The implementation of scheduling techniques requires corresponding metrics to evaluate performance and guide decision-making. Traditional project management literature identifies several established measures for schedule assessment. Herroelen (2004) notes that makespan is utilized as the performance measure for single projects and means project delay (average increase in project completion time relative to initial critical path) as the performance measure for multi-projects. These fundamental metrics provide baseline measures of schedule performance across differing project structures. Addressing broader performance challenges, Herroelen (2004) further observes that projects frequently experience escalation in time and budget, highlighting the need for metrics that can track this escalation. Emphasizing scheduling's multidimensional nature, Miranda & Helia (2019) emphasize that scheduling integrates with other constraints such as budget, scope, and resources, necessitating metrics that capture these interactions. Illustrating the practical impact of effective scheduling, these authors demonstrate tangible schedule improvement in a case study where revised scheduling reduced project completion time by 9 days, from 57 to 48 days (Miranda & Helia, 2019). This case demonstrates the direct relationship between scheduling practice and measurable performance outcomes.

Recent research has expanded the range of metrics to address specialized scheduling requirements. Bosché & Larabi-Tchalaia (2023) identify Schedule Duration Effectiveness and Schedule Accuracy as metrics used throughout project lifecycles to measure scheduling effectiveness. These metrics explicitly balance the competing objectives of schedule compression and reliability. Highlighting the potential unintended consequences of simplistic metrics, Lorko et al. (2020) caution that incentivizing on-time delivery alone may lead to strategic inflation of project schedules, necessitating balance between accuracy and speed incentives. These behavioral dimensions of scheduling metrics underscore the need for multidimensional evaluation approaches. Addressing resource-

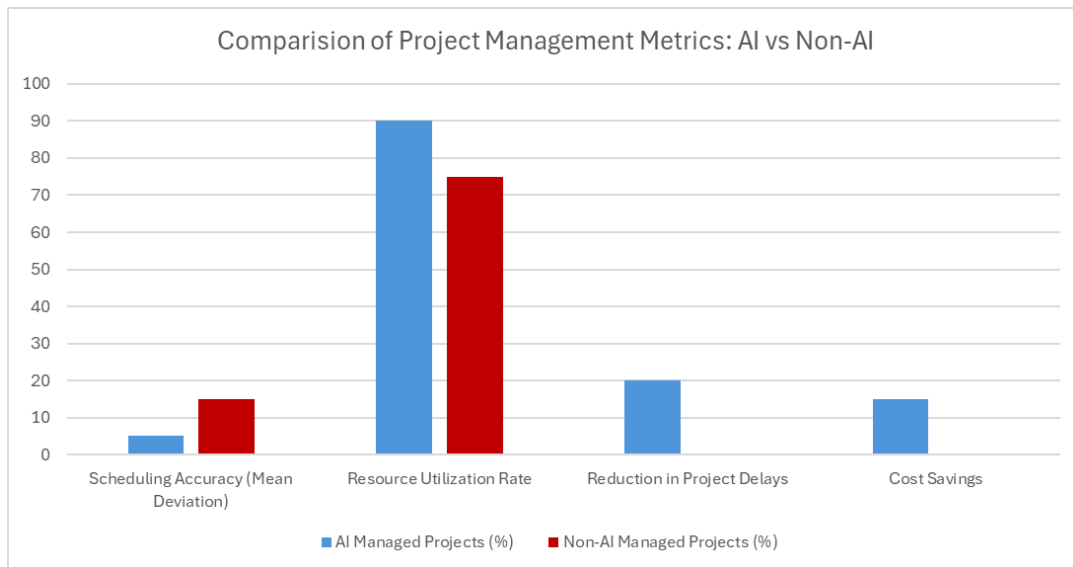
oriented evaluation, Zahedi & Lu (2021) highlight that efficient resource utilization helps streamline resource supply limits and shorten project duration, which proves vital for cost budgeting and earned value management. Expanding this concept with greater technical precision, these researchers further discuss the necessity of defining resource inter-activity utilization efficiency in project scheduling and budgeting (Zahedi & Lu, 2021). This perspective connects schedule performance with resource optimization objectives.

Various specialized metrics address specific dimensions of scheduling performance. Rahman & Elazouni (2015) explain that resource leveling techniques achieve resource leveling efficiency by adjusting project timelines to match resource allocation demands, an approach particularly important in large projects with numerous activities. This efficiency specifically measures the smoothness of resource utilization across the project timeline. Moving beyond operational metrics to financial evaluation, Liu et al. (2024) developed an approach measuring the expected loss of Net Present Value (NPV) due to uncertainties in project scheduling, highlighting NPV's importance in evaluating scheduling effectiveness. This financial perspective directly connects scheduling decisions with economic outcomes, providing a business-oriented evaluation framework.

With the increasing use of predictive models in project scheduling, error-based metrics have gained importance for evaluation. Chen et al. (2016) employ Mean Absolute Percentage Error (MAPE) to validate forecasting model accuracy for Earned Value and Actual Cost, improving predictive power and enabling effective management of project schedules. This approach quantifies the reliability of schedule predictions, essential for confidence in planning decisions. Providing another methodological perspective, Burhan et al. (2021) describe a study developing a mathematical model to forecast repetitive construction projects using Support Vector Machine (SVM), where Root Mean Square Error (RMSE) served as one of three accuracy measurements to compare actual values with predicted values. RMSE provides greater sensitivity to large errors, offering a complementary perspective to MAPE for evaluating predictive models. As advanced computational approaches gain prominence in scheduling, specialized evaluation frameworks emerge. Florence et al. (2024) note that machine learning models utilize metrics like

precision, recall, and F1-score to ensure high accuracy and reliability in detecting delays and improving project management processes. These metrics, drawn from information retrieval and machine learning literature, provide structured approaches to evaluating the classification performance of scheduling models, particularly in identifying potential problems before they impact project performance.

Figure 1 by Egbedion (2024), illustrates AI's performance advantages in project scheduling using some of the key metrics that can be used to estimate scheduling.



**Figure 1 AI vs Non-AI Project Scheduling Metrics (Egbedion, 2024)**

Traditional scheduling techniques, despite their value, struggle with complexity, uncertainty, and dynamism in modern project environments. As Figure 1 demonstrates, AI approaches address these limitations through measurable improvements across key metrics, setting the foundation for exploring artificial intelligence's role in enhancing project scheduling through superior adaptability and optimization capabilities. In the next section we will explore the key aspects of artificial intelligence.

## 2.2 Artificial Intelligence

Artificial intelligence represents a significant domain within computer science. Pournader et al. (2021) describe AI as encompassing the development of computational systems capable of executing functions that would normally require human cognitive abilities. This field has undergone substantial evolution over decades, with researchers

developing diverse approaches to address complex problems across multiple domains, including project scheduling management. The literature demonstrates that a universally accepted definition of AI does not exist (Legg & Hutter, 2007; Nilsson, 2013). Russell & Norvig (2009) propose conceptualizing AI through two principal dimensions: one comparing system performance with either human thinking patterns or ideal rationality, and another examining whether the system matches human capabilities in rational action. From the various conceptualizations proposed throughout AI's history, Minsky's definition from 1968 has gained widespread acceptance for its clarity. As the founder of MIT's Artificial Intelligence Laboratory, he characterized AI as the science of creating machines capable of performing tasks that would demand intelligence when performed by humans. (Minsky, 1968)

### **2.2.1 Evolution of Artificial Intelligence**

In 1955, John McCarthy introduced the concept of "artificial intelligence" as a field studying how machines might perform tasks like using language and solving complex problems normally handled by humans (McCarthy et al., 1955). Looking back at Herbert Simon's 1965 prediction that machines would eventually match human work capabilities, we can observe remarkable progress in AI technologies during the past half-century, with today's systems demonstrating abilities that increasingly align with Simon's forward-looking vision. The field of AI has gained significant momentum due to multiple technological breakthroughs. According to Pournader et al. (2021), three main factors have powered recent AI advances: better computing resources, access to extensive training data from IoT devices, and breakthroughs in learning algorithm design. Major tech companies have further energized this progress, with Google, IBM, Microsoft, and Amazon making large financial commitments to secure leading positions in this growing technological marketplace. When applied to project management, AI provides valuable tools that reshape traditional workflows. Agrawal (2023) highlights how AI helps streamline processes by handling routine tasks automatically, finding better ways to use resources, and supporting more informed decision-making during scheduling. These capabilities help organizations run projects more smoothly while boosting overall performance and results. The benefits of bringing AI into project environments extend beyond simple

efficiency gains. However, as noted by Egbedion (2024), organizations must address certain challenges when implementing AI systems. These include creating strong protection against security threats, planning for possible system failures, and maintaining regular system updates. Despite these hurdles, AI offers substantial advantages through its ability to forecast project timelines with greater accuracy, maximize resource usage, and minimize delays, all contributing to better project outcomes. For information systems projects specifically, AI helps manage complex relationships between tasks and provides data-based insights that support better decisions and improve project performance.

### **2.2.2 An Overview and Introduction to AI Fields**

The world of artificial intelligence includes many specialized areas, each offering unique approaches to solving different types of problems. This section examines the major AI domains relevant to project scheduling applications.

#### **Classical Machine Learning**

Classical Machine Learning forms a central pillar of AI research. As explained by Agrawal et al. (2023), this field develops algorithms that help computers learn patterns from data and make predictions without explicit programming instructions. With nearly 50 years of development behind it, classical machine learning serves as the foundation for many newer AI advances. According to Agarwal & Yadav (2024), these approaches create algorithms that reflect data patterns and help software gradually improve its predictive accuracy over time. Researchers have developed four main learning approaches within machine learning: supervised learning (using labeled data), unsupervised learning (finding patterns in unlabeled data), semi-supervised learning (using both labeled and unlabeled data), and reinforcement learning (learning through environmental feedback) (N. B. Agarwal & Yadav, 2024). Several important algorithms have emerged within supervised learning. Agarwal & Yadav (2024) describe how K-Nearest Neighbors works by storing complete datasets and grouping new data based on its similarity to known examples. Decision Trees handle both classification and regression by creating branching structures that divide data based on different attributes. Random Forest improves on basic decision trees by combining multiple trees and averaging their results, creating more reliable and

accurate predictions. Support Vector Regression adapts classification techniques to predict continuous values by trying to include as many data points as possible within a specified margin around the best prediction line. These approaches help project managers predict important variables like completion times and resource needs based on historical project data.

### **Reinforcement Learning**

Reinforcement Learning takes a different approach to machine intelligence. As described by Agarwal & Yadav (2024), this method teaches models to navigate the environment by taking actions and learning from results, receiving rewards for helpful actions and penalties for harmful ones. Unlike other machine learning approaches, reinforcement learning works without pre-programming or human guidance, allowing systems to discover optimal behaviors through trial and error. This self-improving capability makes reinforcement learning especially useful for project scheduling in changing environments, where teams must constantly adjust plans and reallocate resources as project conditions evolve. Artificial Neural Networks draw inspiration from biological brain structures. Hassanien et al. (2013) describe these networks as mathematical models based on animal nervous systems. They use weighted connections between artificial neurons to process information, similar to how synapses work in biological brains. Each artificial neuron contains several components: an activity level showing its current state, an output value indicating its firing rate, input connections that receive signals, a bias setting that determines its base activation level, and output connections that send signals to other neurons. The network processes information by calculating weighted sums of inputs and applying transformation functions, with learning occurring as connection weights adjust based on experience. These networks excel at finding complex patterns and solving difficult problems, making them valuable tools for finding optimal project schedules in complicated scenarios.

### **Natural Language Processing**

Natural Language Processing focuses on helping machines understand and respond to human language. Agrawal et al. (2023) describe NLP as a machine learning branch that creates algorithms for interpreting and generating human language, supporting

applications like translation and text summarization that would be extremely difficult to program using traditional rules. Recent years have seen major advances in this field. As noted by Yenduri et al. (2024), transformer-based language models represent a breakthrough in creating machines with more human-like language abilities. These systems use attention mechanisms that consider the full context of sentences when generating text, greatly improving their language comprehension and production. For project management, these capabilities help teams analyze project documentation, understand stakeholder communications, and extract valuable knowledge from project records.

### **Swarm Intelligence**

Swarm Intelligence represents a newer AI approach inspired by group behaviors in nature. Ahmed & Glasgow (2012) explain how this field studies the collective actions of simple organisms like ants, bees, and birds, where individuals with limited capabilities follow basic rules to achieve sophisticated group outcomes. This research has led to various nature-inspired algorithms that find efficient solutions to complex problems. Common swarm approaches include Ant Colony Optimization (based on how ants find food using pheromone trails), Particle Swarm Optimization (using groups of simulated particles that move through solution spaces), Artificial Bee Colony (mimicking how bees search for food), and several others. Among these, Particle Swarm Optimization uses collections of virtual particles that adjust their movements based on their own experiences and the discoveries of nearby particles. Ant Colony Optimization models how ants leave chemical trails to mark good paths, allowing the group to collectively find optimal routes. These methods help solve difficult resource allocation and scheduling problems in complex projects with many interacting variables.

### **Evolutionary Algorithms**

Evolutionary Algorithms tackle search and optimization problems using principles from biological evolution. As Hassanien et al. (2013) explain, these methods simulate natural selection through processes like reproduction, mutation, and selection. This family includes genetic algorithms, evolution strategies, and evolutionary programming, all sharing the fundamental concept of improving solutions through simulated evolution. These approaches work especially well for complex optimization tasks in large solution spaces

where traditional methods struggle. According to Eiben & Schoenauer (2002), these algorithms all operate on a similar principle: environmental pressures cause the "survival of the fittest" within a population, gradually improving overall solution quality. This evolutionary approach helps optimize project schedules by finding better ways to sequence tasks and allocate resources while satisfying multiple constraints.

### **Fuzzy Systems**

Fuzzy logic provides tools for dealing with uncertainty and imprecision in decision-making. Zadeh (1965) created this approach to handle the vagueness often found in human language and thinking. Dubois & Prade (1998) explain that fuzzy sets allow partial membership in categories, using values between 0 and 1 to represent degrees of membership rather than strict binary classification. This approach lets elements be partially included in multiple categories, with "less typical" elements receiving intermediate membership values. As noted by Hassanien et al. (2013), fuzzy logic allows more natural expression of human knowledge and reasoning capabilities. This flexibility makes fuzzy logic particularly useful for project scheduling where many parameters contain uncertainty, helping teams model project variables more realistically when precise values aren't available.

### **Optimization and Metaheuristic Algorithms**

Metaheuristic optimization algorithms offer flexible approaches to solving difficult optimization problems. Benaissa et al. (2024) describe these methods as adaptable techniques that work across many problem domains. Unlike traditional optimization methods that require gradient information, metaheuristics can handle problems with non-continuous, noisy, or irregular objective functions. Therefore, technically Benaissa et al. (2024) position these algorithms within the broader AI field focusing on problem-solving strategies for situations where conventional approaches fail. These techniques help optimize complex parameters in structures, systems, and processes, making them valuable for project scheduling optimization. One prominent example, Simulated Annealing, draws inspiration from metal cooling processes. As explained by Benaissa et al. (2024), this algorithm begins searches at a high "temperature" state allowing wide exploration, then gradually "cools" to focus more narrowly on promising solutions. This approach

helps avoid getting trapped in suboptimal solutions when scheduling complex projects with competing objectives.

### **Agent-Based Systems**

Agent-based modeling takes a bottom-up approach to system simulation. Guo & Liu (2024) describe this method as modeling systems by defining individual agent behaviors and their interactions with each other and their environment. This approach appears under several names, including agent-based simulation, agent-based modeling and simulation, multiagent simulation, and multiagent-based simulation (Khodabandelu & Park, 2021; Mazzetto, 2024). According to Khodabandelu & Park (2021), agent-based systems consist of independent decision-making entities, agents, that may represent workers, teams, equipment, or organizations depending on the modeling level. Guo & Liu (2024) note that this approach helps capture emergent system behaviors, understand how individual actions affect system outcomes, and test potential policies in controlled virtual settings. Combining agent-based modeling with other AI techniques improves agent decision-making, behavioral realism, and adaptive capabilities. These features make agent-based approaches valuable for modeling complex project environments with multiple team members and interconnected activities, allowing more realistic simulation of how project teams respond to scheduling constraints.

### **Knowledge Representation and Reasoning**

Knowledge representation and reasoning addresses the challenge of organizing and using complex information effectively. Hommersom & Lucas (2015) explain how early AI systems in healthcare used structured symbolic models, built from expert knowledge, classification systems, and cause-effect relationships, to support diagnosis and treatment decisions. These expert systems laid the foundation for modern approaches that integrate research literature and data analysis to enable human-like reasoning. Among knowledge-based approaches, Bayesian networks have proven particularly effective. As described by Hommersom & Lucas (2015), these networks use directed graphs where nodes represent variables and connecting arrows show dependency relationships. This structure models how the probability of one variable depends on others, allowing systematic reasoning about uncertainty. Bayesian networks use probability calculations to

estimate variable likelihoods and update these estimates when new information arrives. Bahroun et al. (2023) note that these networks now help account for uncertainty and risk in project scheduling, supporting real-time decision-making. They have found applications in critical path calculations and PERT (Program Evaluation and Review Technique) methodologies, demonstrating their value for managing uncertainty in project scheduling and risk assessment.

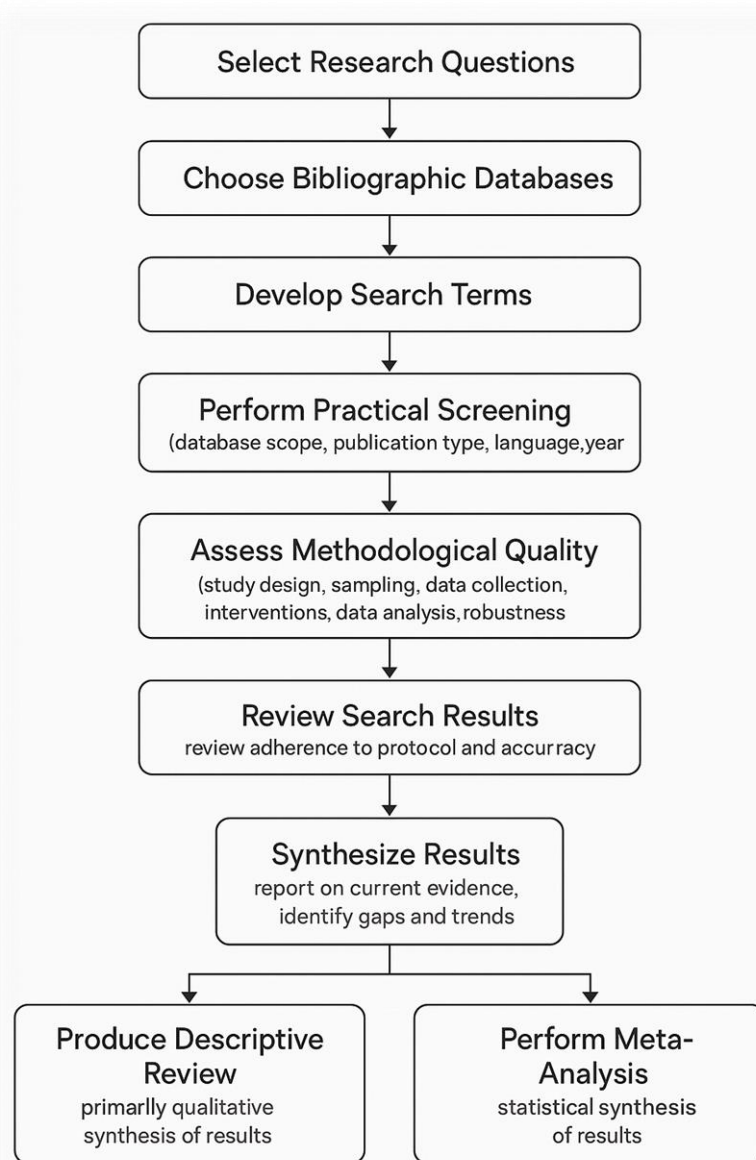
### **3. Research Methodology**

This study employs a systematic literature review (SLR) methodology to investigate the applications and impact of artificial intelligence (AI) in project scheduling within project management. Systematic literature reviews are widely recognized in management research as one of the most efficient and rigorous approaches for identifying, evaluating, and synthesizing relevant literature (Tranfield et al. 2003; Mulrow 1994). As such, this method was chosen for its ability to comprehensively explore and elucidate answers to the research questions while ensuring objectivity and minimizing bias (Tranfield et al., 2003).

The review process undertaken in this research is grounded in the seven-step model proposed by Fink (2019), which is illustrated in Figure 2. This model outlines a structured sequence beginning with the selection of research questions and proceeding through database selection, search term development, screening, review, and synthesis. Each step in the process was executed with transparency and rigor to ensure the quality and reproducibility of findings. Fink (2019) emphasizes that research reviewers must be explicit about their research questions, search strategy, exclusion criteria, data extraction, and synthesis techniques. This principle guided the methodological choices and documentation throughout this review.

The decision to adopt an SLR approach also aligns with the broader aim of describing current research and identifying knowledge gaps without conducting new empirical investigations. As noted by Fink (2019), literature reviews serve not only intellectual or academic purposes but also practical ones, especially when empirical research is not feasible or necessary. In this context, reviewing existing scholarly work on AI in project scheduling was both appropriate and valuable for answering the research questions posed.

Given the interdisciplinary nature of the research topic, spanning artificial intelligence, operations research, and project management, the review required a dynamic and adaptable approach. This is consistent with the view that every research process is unique and must adopt a tailored methodology (Johnson, 2002).



**Figure 2 Adapted Steps to Conduct Research Literature Review (Fink, 2019, p. 5)**

As the review progressed, iterative refinements were made to search for terms, keyword combinations, and inclusion parameters, consistent with Fink's (2019) guidance that the direction of a review may evolve to include new subject headings or author sets in order to broaden the scope and depth of analysis.

To enhance the efficiency and quality of the research process, several AI-powered tools were integrated throughout the systematic literature review. Microsoft Word's AI features were used to refine grammar, improve sentence structure, and assist with

predictive text suggestions, thereby improving overall readability. Microsoft Excel supported the handling of large data sets, offering smart suggestions for visualizations and optimizing data organization. AI language models, including Claude 3.7 Sonnet and ChatGPT, were employed for advanced language tasks such as clarifying complex technical content from academic articles, paraphrasing for improved clarity, and assisting with accurate translation where necessary. Elicit AI was used to implement a triangulated screening process based on a custom-designed protocol, adding an additional layer of validation during the title and abstract screening phase. AsReview Lab supported the semi-automated prioritization of articles during manual review, improving screening efficiency. In addition, search engines and academic databases with AI integration, such as Google Search, Google Scholar, and Scopus AI, were utilized to retrieve semantically relevant and up-to-date publications. These AI-assisted tools provided valuable support across different stages of the review but were not involved in drawing scientific conclusions or interpreting findings, which remained the responsibility of the researcher.

Prior to conducting the search, several academic databases were evaluated for comprehensiveness in the fields of artificial intelligence and project management, including Web of Science, IEEE Xplore, ACM Digital Library, and Scopus. Scopus was selected as the primary database due to its extensive coverage of computer science, engineering, and management literature, holistically, indexing substantial peer-reviewed journals across multiple disciplines. Additionally, a preliminary assessment of search results across databases indicated that Scopus provided the most comprehensive and relevant coverage of articles at the intersection of AI and project scheduling management. The search string was developed through a systematic process. First, an initial list of core concepts was identified based on preliminary reading in the field. Next, these concepts were expanded by identifying synonyms, related terms, and common variants. Several test searches were conducted with different combinations of terms to assess the relevance and volume of results. The search string was refined iteratively, adding wildcards (\*) to capture variations and combining terms with Boolean operators to ensure comprehensiveness while maintaining specificity to the research questions.

**Executed Scopus search query using the formulated search string on peer-reviewed research:**

```
( TITLE-ABS-KEY ( ( "artificial intelligence" OR "machine learning"
OR "deep learning" OR "neural network*" OR "fuzzy logic" OR "rein-
forcement learning" OR "natural language processing" OR "computer
vision" OR "bayesian network*" OR "swarm intelligence" OR "transfer
learning" OR "explainable AI" OR "XAI" OR "agent-based model*" OR
"intelligent system*" OR "knowledge based system*" OR "expert sys-
tem*" OR "intelligent agent*" OR "evolutionary algorithm*" OR "ge-
netic algorithm*" OR "particle swarm optimization" OR "machine
perception" OR "federated learning" OR "transformer model*" OR
"large language model*" OR "multi-agent system*" OR "active learn-
ing" OR "supervised learning" OR "unsupervised learning" ) AND
( "schedul*" OR "schedul* manag*" OR "resource allocat*" OR "time-
line optimiz*" OR "task schedul*" OR "critical path" OR "resource
manag*" OR "resource schedul*" OR "resource optimi*" OR "task al-
location" OR "resource assignment*" OR "resource utilization" )
AND ( "project* management" ) ) )
```

Wildcards (\*) were used to ensure variations of the most important and key terms were not excluded. Further articles were shortlisted based on the following criteria:

Original search query results:	Limited to English language:	Limited to open access:	Limited to Published articles and reviews:	Limited publications to 2015 – 2024:
2036 results	1976 results	343 results	245 results	195 results

Then we exported 195 research paper data to .csv, with complete paper information including abstract. All 195 articles were then downloaded. Initial screening was conducted for access, duplication, retraction, or other issues in complete articles: 2 articles found inaccessible, 1 article found duplicate, and 3 articles found retracted. Furthermore, 1 article was found to be in a non-English language with only abstract in English language. Total number of papers after first review: 188 Articles. After this, the Title and Abstract Screening was done using the following screening criteria:

**Project Management Context:** Does the paper specifically discuss the application within project management rather than in other domains?

**Project Scheduling Focus:** Does the paper address any of these project scheduling aspects: scheduling, schedule management, resource allocation, timeline optimization, task scheduling, critical path, resource management, resource scheduling, resource optimization, task allocation, resource assignment, or resource utilization?

**AI Technique Specificity:** Does the paper explicitly discuss any of these AI-related techniques: artificial intelligence, machine learning, deep learning, neural networks, genetic algorithms, fuzzy logic, reinforcement learning, natural language processing, computer vision, Bayesian networks, swarm intelligence, transfer learning, explainable AI (XAI), agent-based models, intelligent systems, knowledge-based systems, expert systems, intelligent agents, evolutionary algorithms, particle swarm optimization, machine perception, federated learning, transformer models, large language models, multi-agent systems, active learning, supervised learning, or unsupervised learning?

**AI Centrality:** Is AI or machine learning a central focus of the paper rather than just mentioned tangentially?

**Direct Application:** Does the paper clearly demonstrate how AI/ML techniques are directly applied to project scheduling aspects (such as planning, optimization, resource allocation, or critical path analysis) rather than for indirect purposes such as monitoring, estimation or tracking that does not directly optimize scheduling?

**Impact Assessment:** Does the paper address the impact or effects of AI/ML implementation on project scheduling effectiveness or outcomes?

The screening is done three ways for validation and robust process:

1. Manual Screening of Title and Abstract using AsReview Lab for machine learning assistance to increase efficiency: papers selected: 79/188
2. Elicit Screening of Title and Abstract: papers selected: 95/185 [Four papers had parsing issue in Elicit]
3. Claude 3.7 Sonnet Screening of Title and Abstract: papers selected: 96/188

Papers selected in manual screening but rejected by either Elicit or Claude were reviewed against the AI response to verify selection. All 79 papers selected in manual review were found to be relevant with respect to title and abstract screening.

Then manual analysis of title and abstract was done for papers that were excluded in manual screening but included in both the Elicit and Claude screening: 4 papers were further selected based on relevancy. Total number of papers selected after Title and Abstract screening: 83 Articles. The multi-method screening approach combining manual review and independent AI evaluations using Elicit and Claude 3.7 represents a novel

triangulation method for systematic literature reviews. This approach mitigates potential researcher bias and enhances the reliability of the selection process. It also overcomes the researcher's potential lack of depth of knowledge with validation through artificial intelligence as the abstract only gives high level insight into the content of the paper as the more the knowledge of the reviewer the more accurate the relevance and quality review of the paper would be. A total of 112 unique articles were chosen by the three methods out of 188. A total of 73 unique articles were chosen by all three methods out of 122 chosen articles. Therefore, the overlap analysis showed a 65% agreement across all three methods. This innovative approach ensures both efficiency and comprehensiveness in the screening process. Following title and abstract screening, the 83 selected papers underwent a preliminary quality assessment using SCImago Journal Rank metrics to ensure academic rigor. Three metrics were obtained for each paper's journal which were SJR, Quartile and H-Index. Using these three metrics, a quality evaluation framework was created:

**Table 1 Journal Quality Metrics for Quality Assessment of Studies**

SJR Value	Score	Quartile	Score	H-Index Value	Score
$\geq 2.0$	5	Q1	4	$\geq 300$	5
$1.5 \leq \text{SJR} < 2$	4.5	Q2	3	$200 \leq H < 300$	4.5
$1.0 \leq \text{SJR} < 1.5$	4	Q3	2	$150 \leq H < 200$	4
$0.8 \leq \text{SJR} < 1.0$	3.5	Q4	1	$100 \leq H < 150$	3.5
$0.6 \leq \text{SJR} < 0.8$	3	DC	0	$80 \leq H < 100$	3
$0.5 \leq \text{SJR} < 0.6$	2.5			$60 \leq H < 80$	2.5
$0.4 \leq \text{SJR} < 0.5$	2			$40 \leq H < 60$	2
$0.3 \leq \text{SJR} < 0.4$	1.5			$30 \leq H < 40$	1.5
$0.2 \leq \text{SJR} < 0.3$	1			$20 \leq H < 30$	1
$0.1 \leq \text{SJR} < 0.2$	0.5			$10 \leq H < 20$	0.5
$\text{SJR} < 0.1$	0			$H < 10$	0
Discontinued (DC)	0				

And using the framework, the combined value index for each research paper was calculated using the following formula:

$$\text{Total\_Score} = [(\text{SJR\_Score}) + (\text{Qrt\_Score}) + (\text{H-I\_Score})] / 14 \times 100$$

It was found that out of a total of 83 journals, a total of 28 journals were ranked below 50% whereas 55 journals were ranked more than 50%. This shows that the research consists of research papers from journals of high quality with very good impact and reach. After this, all the research papers from journals with ranking of less than 50% were reviewed further in depth through their introduction and conclusion section to check for their relevancy to the screening criteria. For this, the initial screening criteria were detailed further as follows:

**Table 2 Initial Screening Criteria for Relevance Review**

Project Management Context	1.0: Clear, explicit project management focus.
	0.0: Project management mentioned but not comprehensively addressed or shares focus with other domains non-project related or no clear project management context or primarily focused on domains other than project related.
Project Scheduling Focus	1.0: In-depth coverage of at least one project scheduling aspect.
	0.0: Some coverage of project scheduling but lacks depth or is not a primary focus or minimal or no project scheduling aspects addressed.
AI Technique Specificity	1.0: Detailed explanation of at least one specific AI technique with technical details.
	0.0: Mentions specific AI techniques but all of them with limited technical detail, none with technical details or vague mention of AI or no specific techniques identified.
AI Centrality	1.0: AI is clearly the central focus of the paper with substantial technical content dedicated to it.
	0.0: AI is non-important, and shares focus equally with non-AI aspects or AI is peripheral, minimally addressed, or merely mentioned.
Direct Application	1.0: Clear demonstration of AI applied directly to scheduling or related facets.
	0.0: Vague connection between AI and scheduling or related facets or no direct application of AI to scheduling problems, only conceptual mention, or applying AI for indirect purposes such as monitoring, estimation or tracking that does not directly optimize scheduling.
AI Impact Assessment	1.0: Comprehensive assessment of AI impact with quantitative metrics, evidence, or comparison to baseline methods that are clear and distinct.
	0.0: Some discussion of AI impact but limited evidence or metrics or no assessment of AI impact on scheduling effectiveness.

Papers from journals of lower quality yet with high relevance were retained for methodology review. After the review, 15 out of 28 papers were selected from the lower quality journals that were of high relevance.

Total number of papers selected after Journal Quality and Relevance Review: 70 Articles  
After the journal quality review and relevance review, the methodology and research quality review were conducted.

In order to conduct this review, two screening criteria were developed:

**Table 3 Final Screening Criteria for Methodological Robustness Review**

Methodological Rigor	1.0: Robust methodology with clear design, appropriate methods, systematic approach, and validation
	0.0: Acceptable methodology but with some limitations or gaps or poor methodology, unclear approach, or significant methodological flaws
Evidence Quality	1.0: Strong empirical evidence with appropriate datasets, validation, statistical analysis, or clear results
	a. 0.0: Almost no evidence and limited in scope, size, or analysis or no evidence provided at all

After the methodology and research quality review on the remaining 70 results, using the screening criteria, a total of 66 out of 70 papers were selected as these papers met all the minimum quality threshold and therefore a total of 66 papers were retained for full-text review and synthesis. Total number of papers selected after methodology and quality review: 66 Articles. Out of the selected 66 journals, 33 are from Q1, 22 are from Q2, 6 are from Q3, and 5 are from Q4. The study followed a structured multi-stage screening process to identify relevant literature on the application of AI techniques in project scheduling within project management. The selection process, summarized in Figure 3, includes keyword-based database search, data cleaning, screening, journal quality filtering, and methodological assessment.

The systematic literature review implemented appropriate documentation protocols throughout the research process, facilitating methodological consistency from initial database querying through final paper selection. Structured evaluation frameworks were employed for quality assessment across all considered articles, with consistent application of the predefined criteria. Standard data extraction methods ensured uniformity in information retrieval, supported by verification mechanisms to minimize transcription

errors. These methodological considerations align with established best practices in systematically reviewing documentation, enhancing the analytical rigor and reproducibility underpinning the study's findings and conclusions.

The analysis in this review was conducted using qualitative and descriptive synthesis. The chosen approach allowed for a comprehensive overview of the selected studies, aiming to highlight emerging insights and reinforce existing knowledge in AI-based project scheduling.

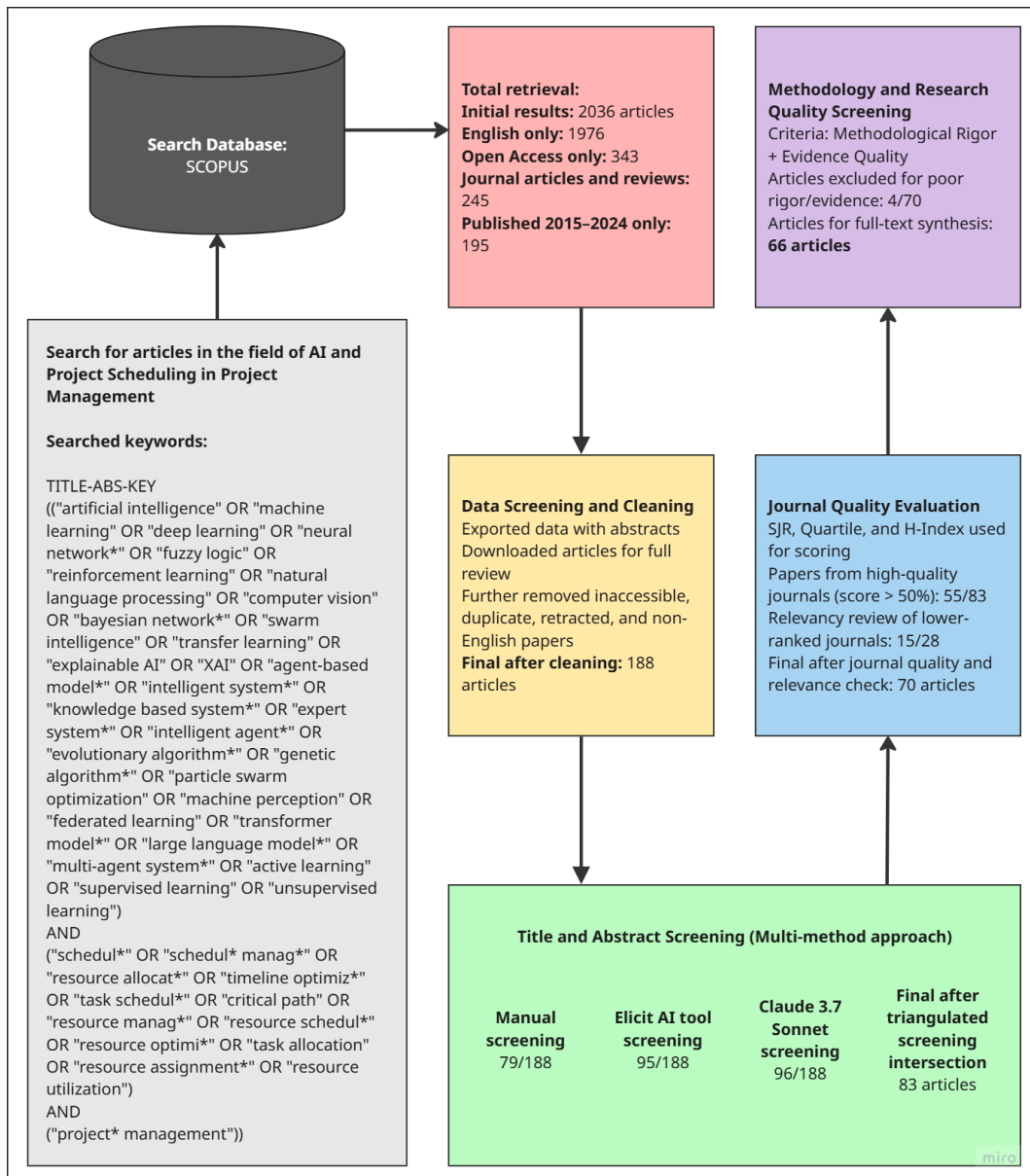


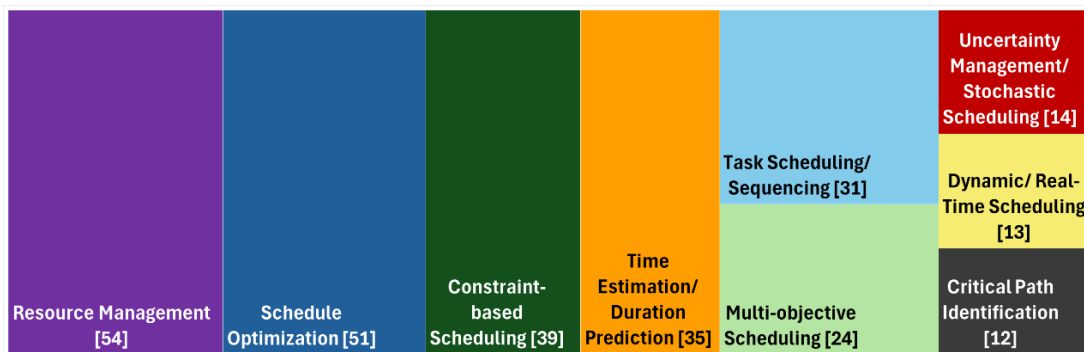
Figure 3 SLR Flowchart for Study Selection Process

## 4. Findings and Analysis

This chapter states the findings and analysis of the selected studies.

### 4.1 Project Scheduling Functions

Based on theoretical grounding and systematic review, nine distinct AI-supported scheduling functions were identified, each serving a unique purpose. Figure 4 shows the frequency of focus for scheduling functions across selected studies.



**Figure 4 Scheduling Function Focus Across the Studies**

Resource Management stands out by focusing on how labour and assets are distributed, rather than task order or timing. Schedule Optimization differs by aiming to enhance the schedule, rather than addressing isolated aspects like constraints or resources. Constraint-Based Scheduling is defined by its strict adherence to predefined rules, setting it apart from more flexible or outcome-driven functions. Time Estimation and Duration Prediction supports scheduling by generating the time inputs, rather than organizing or optimizing tasks. Task Scheduling and Sequencing emphasizes on ordering activities, not forecasting durations or balancing objectives. Multi-Objective Scheduling is unique in handling trade-offs between competing goals, unlike single-target approaches. Uncertainty Management and Stochastic Scheduling accounts for variability, in contrast to models assuming fixed conditions. Dynamic and Real-Time Scheduling operates during execution, unlike pre-planned models that lack responsiveness. Critical Path Identification plays a diagnostic role, supporting rather than constructing the schedule itself. found.

## 4.2 AI Techniques Implemented

A total of 10 AI fields comprising of a total of 70 unique AI techniques were found from the reviewed articles as shown in Table 4, Table 5 and Table 6. Furthermore, table 7 presents the article wise distribution of AI fields and Project Industries for single method AI implementations while table 8 shows the same for hybrid method AI implementations.

**Table 4 AI Fields Grouping of Investigated Techniques**

Short Form	Category
ABS	Agent Based Systems
CML	Classical Machine Learning Models
EA	Evolutionary Algorithms
FS	Fuzzy Systems
GPT	Generative Pre-Trained Transformer
KNR	Knowledge Representation and Reasoning
NN	Neural Networks
OM	Optimization and Metaheuristics
RL	Reinforcement Learning
SI	Swarm Intelligence

**Table 5 AI Technique Distribution by Usage Freq. and AI Fields – Section 1**

Agent Based Systems		Fuzzy Systems		Generative Pre-Trained Transformer		Knowledge Representation and Reasoning		Reinforcement Learning	
Multi Agent Systems	2	Fuzzy logic	3	GPT-J Large Language Model	1	Bayesian Network	2	Reinforcement Learning Algorithm	3
Agent-Based Modeling	2	Adaptive Network based on the Fuzzy Inference System	1	GPT-3.5 Large Language Model	1			Deep Q Network with Dynamic Feedback Mechanisms	1
		Fuzzy Clustering	1	GPT-4 Large Language Model	1			Deep Q-Network	1
		Fuzzy C-Means Clustering	1					Deep Reinforcement Learning	1
		Fuzzy Earned Value Management	1					Valid Action Sampling	1
		Linear Diophantine Fuzzy Sets	1						
		Parallel Structure based on the Fuzzy System	1						



Table 7 AI Field and Industry Distribution by Paper in Single-Method

ID	EA	NN	SI	OM	CML	FS	RL	ABS	GPT	KNR	Project Industry Implementation
P01	1										Software development projects
P02		1									Industry not clearly specified
P03	1										Real estate development projects
P04	1										Aerospace industry projects
P05		1									Industry not clearly specified
P06			1								Hydropower industry projects
P07	1										Precast construction projects
P08		1									Construction industry projects
P09									1		Software development projects
P10		1									Construction industry projects
P11							1				Industry not clearly specified
P12	1										Construction industry projects
P13	1										Manufacturing projects for complex equipment
P14	1										Construction, Production, and Manufacturing industry projects
P15					1						Construction and Information Systems industry projects
P16			1								Software development projects
P17							1				Engineering projects
P18			1								Construction industry projects
P19						1					Construction industry projects
P20									1		Construction industry projects
P21						1					Agricultural Manufacturing projects
P22				1							Construction industry projects
P23							1				Construction, Defense, and Aerospace industry projects
P24	1										Software development projects
P25	1										Construction industry projects
P26						1					Construction industry projects, Garment industry projects
P27	1										Construction industry projects
P28	1										Construction industry projects
P29		1									Highway Construction industry projects
P30	1										AI and IoT projects; Software development projects
P31	1										Construction industry projects
P32	1										Construction industry projects
P33		1									Construction industry projects
P34					1						Software development projects
P35									1		Digital technology sector projects
<b>Usage Freq.</b>	<b>14</b>	<b>6</b>	<b>3</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>3</b>	<b>0</b>	<b>3</b>	<b>0</b>	
<b>ID</b>	<b>EA</b>	<b>NN</b>	<b>SI</b>	<b>OM</b>	<b>CML</b>	<b>FS</b>	<b>RL</b>	<b>ABS</b>	<b>GPT</b>	<b>KNR</b>	

Table 8 AI Field and Industry Distribution by Paper in Hybrid-Method

ID	EA	NN	SI	OM	CML	FS	RL	ABS	GPT	KNR	Project Industry Implementation
P36		1					1				Construction industry projects
P37		1			1						Construction industry projects
P38	1		1								Construction industry projects
P39	1			1							Construction industry projects
P40	1							1			Maintenance, Service, Supply Chain and Manufacturing projects
P41		1				1					Construction industry projects
P42	1					1					Construction industry projects
P43	1		1								Construction industry projects
P44			1	1							Highway construction industry projects
P45		1					1				Construction industry projects
P46		1	1		1						Software development projects
P47		1			1						Construction industry projects
P48	1	1				1					Construction industry projects
P49				1	1						Construction industry projects
P50	1			1							Software development projects
P51	1				1			1			Construction industry projects
P52	1					1					Construction industry projects
P53	1			1							Software development and IT projects
P54		1								1	Construction industry projects
P55	1		1					1			Industry not clearly specified
P56	1		1								Industry not clearly specified
P57		1				1					Construction industry projects
P58			1		1			1			Construction industry projects
P59		1				1					Industry not clearly specified
P60	1			1							Construction industry projects
P61				1						1	Construction industry projects
P62				1	1						Construction industry projects
P63	1	1	1								Construction industry projects
P64	1		1	1							Information system projects
P65				1	1						IT infrastructure projects, Construction industry projects
P66	1		1								Internet research and development projects
<b>Usage Freq.</b>	<b>16</b>	<b>11</b>	<b>10</b>	<b>10</b>	<b>8</b>	<b>6</b>	<b>2</b>	<b>4</b>	<b>0</b>	<b>2</b>	
<b>ID</b>	<b>EA</b>	<b>NN</b>	<b>SI</b>	<b>OM</b>	<b>CML</b>	<b>FS</b>	<b>RL</b>	<b>ABS</b>	<b>GPT</b>	<b>KNR</b>	

### **4.3 Single-Method AI System Implementation and Impact**

In this review, Single-Method AI Systems refer to approaches that utilize one or more techniques within the boundaries of a single AI field. Examples of fields include Reinforcement Learning (RL), Neural Networks (NN), and Swarm Intelligence (SI), among others. Although multiple algorithms or models may be used, they are drawn exclusively from the same overarching category. This design allows a focused evaluation of how particular AI paradigms individually contribute to project scheduling, without cross-domain integration. It ensures that improvements, limitations, and innovations are attributed specifically to the strengths and weaknesses of that single AI field.

#### **4.3.1 Evolutionary Algorithm**

Evolutionary Algorithms (EAs) constitute a branch of artificial intelligence that employs principles of biological evolution to solve complex optimization problems. The systematic literature review identified 13 papers utilizing evolutionary techniques for project scheduling optimization, with Genetic Algorithms (GAs) representing the predominant approach (12 papers). These techniques function through iterative population-based search processes involving selection, crossover, and mutation operations to evolve progressively better scheduling solutions. Several distinct variants emerged across the analyzed papers: traditional GAs (Anvari et al., 2016; Qiao et al., 2021; Caglayan & Yigit, 2024; He et al., 2021), multi-objective optimization through Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Li et al., 2018; Abdelbasset et al., 2023; Zhang et al., 2024), Genetic Programming (GP) for evolving priority rules (Chen et al., 2022), and Estimation of Distribution Algorithms (EDAs) that build probabilistic models of promising solutions. A notable trend observed was the prevalence of hybrid implementations, where evolutionary methods were combined with other techniques: NSGA-II with steepest descent heuristics (H. Li et al., 2018), GAs with Monte Carlo simulation (Ma et al., 2019), and hyper-heuristic frameworks guiding evolutionary search (Chen et al., 2022). The chronological progression revealed increasing sophistication in addressing multiple competing objectives simultaneously, particularly cost-time-quality tradeoffs, alongside enhanced constraint handling mechanisms.

### **Implementation in Project Scheduling**

Evolutionary algorithms have been implemented across diverse project types to address complex scheduling challenges. In software development projects, researchers applied Genetic Algorithms to optimize multi-objective resource-constrained project scheduling problems through compromise programming (Son et al., 2021). Son et al. (2021) transformed objectives of minimizing makespan, cost, and maximizing quality into a single objective using normalized deviations from ideal values for time, cost, and quality. For real estate development projects, evolutionary algorithms optimized activity sequences within a Design Structure Matrix framework to minimize expected feedback distance (Ma et al., 2019). Ma et al. (2019) configured their algorithm with a population of 100 individuals evolved over 200 generations, using crossover and mutation probabilities of 0.95 and 0.08 respectively.

The implementation of evolutionary techniques in aerospace manufacturing demonstrated sophisticated adaptations. Chen et al. (2022) combined Genetic Programming with multi-objective evolutionary optimization to evolve priority rules for scheduling problems with stochastic activity durations. These rules were structured as decision trees with nodes representing scheduling attributes and functional operations. Chen et al. (2022) further enhanced this approach with a Hyper-Heuristic Framework incorporating two-stage filtering to guide the search process by eliminating irrelevant attributes and constraining tree depth.

Construction industry applications revealed diverse implementation strategies across multiple studies (Anvari et al., 2016; Li et al., 2018; Lazari et al., 2024; Pham & Duong, 2023; Abdelbasset et al., 2023; Elkliny et al., 2023). Anvari et al. (2016) modeled precast construction scheduling as a Resource-constrained Extended Flexible Job Shop Scheduling problem, using a specialized chromosome structure encoding both task-resource assignment and operation sequencing. H. Li et al. (2018) introduced an innovative critical path-based crossover operator ensuring that genetic recombination prioritized activities most influencing project duration and cost. Lazari et al. (2024) operationalized Genetic Algorithms in a spreadsheet structure using Palisade Evolver software integrated into Excel with a population size of 50 and crossover and mutation rates of 0.5 and 0.1

respectively. Pham & Duong (2023) encoded execution time and lag time between dependent tasks to optimize construction progress schedules, while Abdelbasset et al. (2023) implemented NSGA-II to optimize crew numbers and work sequences using the Distributed Evolutionary Algorithms in Python framework. Elkliny et al. (2023) employed Genetic Algorithms through an Excel-based optimization tool called "SolveXL" to select optimal construction methods for each activity and determine activity start times under resource constraints.

Manufacturing projects demonstrated another important application domain (Qiao et al., 2021; Caglayan & Yigit, 2024; He et al., 2021). Qiao et al. (2021) transformed the resource leveling problem into a multi-path selection problem, treating scheduling choices for non-critical activities as genes with an enhanced block crossover mechanism to maintain population diversity. Caglayan & Yigit, (2024) operationalized Genetic Algorithms in MATLAB to optimize project crashing, with decision variables indicating allowable crashes per activity and an objective function combining direct and indirect costs. W. He et al. (2021) applied Genetic Algorithms across multiple workspaces, assembly, logistics, and production, in prefabricated building projects to solve time-cost trade-off problems while ensuring synchronization between different phases.

Recent implementations have shown increasing sophistication. Zhang et al. (2024) utilized an improved NSGA-II for AI and IoT software development projects with a two-layer chromosome encoding structure mapping engineers to projects and specific activities. H. Li & Dong (2018) developed a hybrid Estimation of Distribution Algorithm that built and sampled from probabilistic models characterizing promising solutions, integrating traditional Genetic Algorithm operators like crossover and mutation alongside the probabilistic sampling.

### **Impact on Project Scheduling Effectiveness**

Evolutionary algorithms have demonstrated significant improvements in project scheduling performance across multiple domains. In software development contexts, Genetic Algorithms effectively balanced critical path duration, project cost, and team experience while substantially reducing computational effort compared to exhaustive search methods (Son et al., 2021). Son et al. (2021) achieved critical paths as low as 555-571 units

with project costs around \$287,000-307,000 and experience scores between 6420-6506, completing optimization in 659 milliseconds versus 335,787 milliseconds for brute-force approaches. H. Li & Dong (2018) reported superior performance of their hybrid Estimation of Distribution Algorithm over traditional genetic algorithms for resource leveling problems with generalized precedence constraints, particularly for larger project networks with varying degrees of resource constraint tightness.

Integration with simulation techniques enhanced scheduling robustness under uncertainty for real estate development projects (Ma et al., 2019). Ma et al. (2019) demonstrated that Genetic Algorithms reduced expected feedback distance from 42 to 36.8 and total feedback distance from 193 to 166 compared to unoptimized sequences, while Monte Carlo simulation enabled precise estimation of project completion probabilities with 90% confidence through calculated project buffers.

For aerospace manufacturing, evolutionary techniques outperformed traditional scheduling methods by significant margins (Chen et al., 2022). Chen et al. (2022) reported that their Genetic Programming with multi-objective optimization approach produced more effective and customized scheduling policies under stochastic disturbances. Their Hyper-Heuristic Framework further improved convergence rates and solution quality, proving particularly valuable for high-variance, uncertain project scenarios requiring adaptability. Construction industry applications consistently demonstrated measurable benefits across multiple studies (Anvari et al., 2016; Li et al., 2018; Lazari et al., 2024; Pham & Duong, 2023; Abdelbasset et al., 2023; Elkliny et al., 2023). Anvari et al. (2016) found that Genetic Algorithms enabled holistic optimization of manufacturing, transportation, and assembly sectors in precast construction, producing near-optimal schedules faster than exact methods like Mixed Integer Linear Programming. H. Li et al. (2018) showed significant improvements in scheduling flexibility and time-cost trade-off options despite standalone steepest descent heuristics outperforming pure NSGA-II in their experiments. Lazari et al. (2024) achieved reductions in resource overallocation to approximately 3% of total resource units and day-to-day resource movements to about 7.5%, indicating smoother resource utilization. Pham & Duong (2023) reported a 56.83% reduction in project duration and 38.39% lower maximum labor requirement compared to initial

random schedules. Abdelbasset et al. (2023) validated their NSGA-II model through a benchmark project and real-life case study, demonstrating an 8% reduction in project duration and 0.78% reduction in overall cost. Elkliny et al. (2023) produced schedules reducing project duration by 5 days while satisfying resource constraints, improving resource leveling, and enhancing project quality by 0.36%.

Manufacturing projects showed similarly impressive results from evolutionary optimization (Qiao et al., 2021; Caglayan & Yigit, 2024; He et al., 2021). Qiao et al. (2021) achieved significant balancing of resource usage across multiple concurrent projects, decreasing peak resource demands and minimizing variance in resource usage patterns. Caglayan & Yigit, (2024) found their Genetic Algorithm approach reached optimal project duration and cost in a single computational phase, achieving a project duration of 17 days and minimized cost of \$25,675 more efficiently than traditional multi-phase manual crashing processes. W. He et al. (2021) reported substantial improvements in prefabricated building projects, with construction time reduced by 19.9% and cost by 9% compared to traditional planning methods.

In AI and IoT software development projects, Zhang et al. (2024) demonstrated that their improved NSGA-II implementation achieved approximately 7% reduction in average project duration and 13% enhancement in workload balance compared to classical NSGA-II. Zhang et al. (2024) further reported up to 9% shorter project duration and 40% better balance in scenarios prioritizing either objective, translating into better scheduling efficiency and more effective use of multi-skilled human resources.

The consistent positive impacts across diverse project environments confirm evolutionary algorithms as powerful tools for project scheduling optimization. Their ability to efficiently navigate large solution spaces and balance competing objectives has established them as a widely applied AI approach in contemporary project scheduling management.

### **4.3.2 Neural Network**

Neural networks represent a significant artificial intelligence approach in project scheduling management, drawing inspiration from biological neural systems to process complex project data patterns. The literature demonstrates diversification in neural network

architectures tailored to specific scheduling challenges. Convolutional Neural Networks (CNNs) have been applied to recognize spatial patterns in project parameters for priority rule selection (Golab et al., 2023), while Multilayer Feed-Forward Neural Networks (MLFNNs) have been employed for similar decision support functions with different architectural configurations (Gooya et al., 2022). Traditional Artificial Neural Networks (ANNs), including multilayer perceptrons trained with Scaled Conjugate Gradient algorithms, have found application in construction project duration prediction (Ozkan & Gulcicek, 2015) and delay forecasting (Waheeb et al., 2020; Jasim et al., 2020). More specialized architectures like Radial Basis Function (RBF) neural networks have been implemented in hybrid systems alongside Reference Class Forecasting methodologies to predict post-disruption recovery patterns (Chen et al., 2024). A discernible trend across these implementations is the evolution from general-purpose ANN applications toward more specialized architectures tailored to specific scheduling sub-problems, with increasing emphasis on predictive analytics for project trajectory forecasting rather than optimization of current-state scheduling decisions.

### **Implementation in Project Scheduling**

Neural networks have been operationalized within the context of project scheduling across various further implementation contexts, with specific architectural variants tailored to distinct scheduling challenges. In resource-constrained project scheduling problems (RCPS), both Convolutional Neural Networks and Multilayer Feed-Forward Neural Networks have been implemented for priority rule selection during project execution (Golab et al., 2023; Gooya et al., 2022). These approaches process eight project-specific parametric inputs recalculated at each scheduling step, including network complexity, resource factors, and percentage of remaining work. H. structured their MLFNN with two hidden layers employing rectified linear unit (ReLU) activation functions and a sigmoid activation function at the output layer, while Golab et al. (2023) implemented a CNN architecture specifically designed to recognize spatial patterns within project parameter data for more sophisticated decision-making during scheduling steps.

In construction industry applications, neural networks have been configured as predictive tools for various scheduling metrics using diverse architectural approaches (Ozkan

& Gulcicek, 2015; Waheeb et al., 2020; Chen et al., 2024; Jasim et al., 2020). Ozkan & Gulcicek (2015) implemented a multilayer feedforward perceptron trained using the Scaled Conjugate Gradient (SCG) algorithm to predict project durations, systematically testing configurations with varying hidden layers (1-4) and training epochs (1000-3000). Waheeb et al. (2020) developed an ANN model with twelve identified delay factors as inputs to a three-node hidden layer architecture, operationalized through a JavaScript-based application for practitioner use. Chen et al. (2024) combined Radial Basis Function (RBF) neural networks with Reference Class Forecasting (RCF) methodology, building their model with inputs including project budget, planned duration, risk levels, and pre-disruption performance metrics. For highway construction specifically, Jasim et al. (2020) implemented a three-layer feedforward network to predict the To Complete Schedule Performance Indicator (TCSPI) using Budget at Completion (BAC), Earned Value (EV), and Planned Value (PV) as inputs, utilizing GMDH Shell software with a 75%-15%-10% split for training, testing, and validation datasets.

### **Impact on Project Scheduling Effectiveness**

Empirical evaluations reveal that neural networks achieve varying levels of scheduling prediction accuracy depending on their application context. Chen et al. (2024) demonstrated that their RBF neural network predicted project recovery patterns with over 95% accuracy and minimal errors (below 5%), allowing project managers to reliably forecast how projects would recover after disruptions. Their approach significantly outperformed traditional forecasting methods, particularly in capturing complex recovery trajectories. Similarly, Jasim et al. (2020) documented that their neural network predicted schedule performance indicators for highway construction with over 93% accuracy, enabling contractors to accurately forecast whether remaining work could be completed within scheduled timeframes. Both studies confirmed that neural networks excel at forecasting specific schedule metrics with high precision, though they focused on different aspects of project scheduling.

Studies examining neural networks for priority rule selection highlight a trade-off between computational speed and absolute performance. Golab et al. (2023) found that CNNs generate high-quality schedules without needing to evaluate multiple solution

alternatives, significantly reducing computation time. Their CNN approach performed particularly well for larger projects compared to previous methods, showing better scalability as project complexity increased. Gooya et al. (2022) quantified the performance gap, showing their neural network produced schedules about 16% longer than optimal for medium-sized projects and about 38% longer for large projects. Both studies concluded that while neural networks do not produce the absolute shortest schedules compared to more complex algorithms, they create reasonably good schedules much faster, making them practical for time-sensitive planning scenarios.

Construction-focused applications demonstrate valuable but more modest predictive benefits. Ozkan & Gulcicek (2015) achieved approximately 70% accuracy in predicting which scheduling strategy would produce the shortest project duration, which they emphasized represents significant practical value given construction's inherent variability. Waheeb et al. (2020) reported similar accuracy levels (about 65%) for predicting both cost overruns and time delays in emergency reconstruction projects. These studies suggest neural networks can reliably identify potential schedule and cost issues in advance, though with higher uncertainty than in more controlled environments. Both research teams emphasized that even this moderate level of predictive capability provides substantial practical value by enabling proactive management interventions.

A key advantage documented across all implementations is the fundamental shift from reactive to proactive scheduling approaches. Jasim et al. (2020) and Chen et al. (2024) emphasized that early identification of potential schedule deviations was their primary contribution to project management practice. Gooya et al. (2022) and Golab et al. (2023) highlighted how neural networks enable adaptive scheduling strategies that respond to changing project conditions. Ozkan & Gulcicek (2015) and Waheeb et al. (2020) both stressed that neural networks allow project managers to anticipate problems and select mitigation strategies before schedule implementation begins. Despite differences in specific neural network types and application contexts, all studies converged on this critical finding: neural networks transform traditional schedule management from a reactive exercise to a predictive practice through their ability to recognize patterns that human planners might miss.

### 4.3.3 Swarm Intelligence

Swarm intelligence techniques represent a significant class of metaheuristic approaches employed in project scheduling optimization. These nature-inspired computational methods leverage collective behavior patterns observed in biological systems to solve complex optimization problems. Analysis of the selected literature reveals prominent application of three key swarm intelligence variants: traditional Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Quantum-behaved Particle Swarm Optimization (QPSO). Each technique demonstrates distinctive evolutionary computation characteristics tailored to address specific project scheduling constraints (Zhang et al., 2016; W. Zhang et al., 2018; Wang et al., 2020). The predominant trend observed across these studies is the development of specialized algorithmic variants adapted to the unique multi-objective and constraint-handling requirements of project scheduling domains.

#### Implementation in Project Scheduling

Swarm intelligence techniques have been implemented across diverse industry contexts with sophisticated adaptations to address domain-specific scheduling challenges. In hydropower industry applications, Zhang et al. (2016) implemented a Bi-level Global-Local-Neighbor Particle Swarm Optimization (BGLN-PSO) algorithm that handles hierarchical decision-making structures through separate optimization levels: upper-level decision makers focus on minimizing project makespan and maximizing profit, while lower-level decision makers concentrate on operational cost minimization. The algorithm was specifically tailored to optimize investment and task timing decisions under uncertainty conditions using Dependent-Chance Programming (DCP) for practical implementation in hydropower construction scheduling. For software development environments, adaptive Ant Colony Optimization algorithms were deployed to facilitate employee rescheduling across concurrent projects, utilizing pheromone-based selection mechanisms and pre-selection rules to efficiently match employee skills with delayed activities (Zhang et al., 2018). Zhang et al. (2018) further demonstrated how these mechanisms support project managers in making resource allocation decisions without disrupting concurrent project schedules, enabling artificial ants to construct feasible rescheduling solutions by

selecting employees based on pheromone levels and heuristic evaluations of skill match and availability. In construction industry contexts, Z. Wang et al. (2020) implemented QPSO within a two-stage optimization framework specifically configured for resource leveling in linear projects. Z. Wang et al. (2020) incorporated dynamic constraint handling mechanisms and search scope restrictions to ensure scheduling feasibility while managing the complex interdependencies of construction activities. This implementation addressed the discrete, constrained, and highly nonlinear characteristics of resource leveling by integrating a dimension unification technique to maintain consistent solution dimensionality, particularly important for noncontrolling segments of construction activities.

### **Impact on Project Scheduling Effectiveness**

The implementation of swarm intelligence techniques has demonstrated significant quantitative and qualitative impacts on project scheduling effectiveness. BGLN-PSO applications in hydropower projects yielded measurable improvements in convergence speed and solution stability, enabling more balanced decision-making between project duration and profitability under uncertainty conditions (Z. Zhang et al., 2016). Zhang et al. (2016) reported that this approach provided faster search times with fewer iterations while producing more stable results across multiple execution runs, particularly evident in applications to the Grounding Grid System Project at Jin' An Qiao hydropower station. The bi-level structure allowed more realistic modeling of hierarchical decision-making, while the robust search capabilities directly enhanced project scheduling efficiency and reduced risks associated with local minima entrapment.

The adaptive ACO approach achieved substantial delay reductions, with experimental results showing average delay decreases of 46% across benchmark datasets and complete delay elimination in some instances, while maintaining schedule stability without requiring overtime work (Zhang et al., 2018). Zhang et al. (2018) documented that in real-world case studies, their adaptive ACO implementation achieved a 75.2% average delay reduction while simultaneously minimizing delay propagation risks across concurrent projects. The approach demonstrated superior performance relative to both basic ACO and genetic algorithms, consistently achieving higher feasible solution rates ("hit

counts") even as project scale increased. This adaptability to project complexity represents a significant advantage for software development contexts where resource constraints and interdependencies frequently present scheduling challenges.

The QPSO implementation in construction scheduling demonstrated superior resource utilization metrics compared to conventional techniques, producing significantly reduced daily resource fluctuations and lower peak resource requirements (Z. Wang et al., 2020). Z. Wang et al. (2020) verified these improvements through comparative case studies where QPSO-based optimization consistently outperformed PSO and other existing models in achieving the lowest objective function values for resource leveling quality. A cross-comparative analysis reveals complementary strengths across these swarm intelligence variants. While BGLN-PSO excels in handling multi-objective optimization with hierarchical constraints (Z. Zhang et al., 2016), adaptive ACO demonstrates particular efficacy in dynamic rescheduling scenarios requiring minimal disruption (Zhang et al., 2018), and QPSO offers superior performance in resource-constrained environments requiring fine-grained optimization (Z. Wang et al., 2020). Collectively, these studies demonstrate that swarm intelligence techniques offer robust search capabilities particularly well-suited to complex, multi-constraint project scheduling environments across diverse industrial contexts.

#### **4.3.4 Optimization and Metaheuristic**

Optimization and metaheuristic techniques represent a significant category of artificial intelligence approaches applied to project scheduling management. These techniques are particularly valuable for solving complex, combinatorial optimization problems that arise in project scheduling where traditional methods may be computationally infeasible. Metaheuristics provide approximation algorithms that can efficiently navigate large solution spaces to find near-optimal solutions without exhaustively evaluating all possibilities. Among these techniques, Tabu Search (TS) has emerged as a powerful metaheuristic optimization algorithm capable of addressing the multifaceted challenges inherent in project scheduling, particularly in construction environments with complex resource allocation requirements and strict temporal constraints.

### **Implementation in Project Scheduling**

The implementation of Tabu Search as a decision-support tool has demonstrated significant potential in complex scheduling environments (Podolski, 2017). This implementation addressed an NP-hard scheduling problem structured as a hybrid flow shop with multiple working groups per work type, non-permutation unit orders, and precedence constraints modeled through a directed acyclic graph. Notably, the search process was initiated with randomly generated schedules, with moves defined as "insertions" of units between sequences of working groups. Podolski (2017) employed a tabu list mechanism to prevent cycling during the search process, recording move attributes based on job positions and resource groups to ensure the algorithm did not revisit previously explored solutions. The neighborhood exploration phase involved all insertion moves on randomly selected working group sequences, with the best admissible move (determined by the smallest project makespan) being iteratively selected. The implementation was executed in the Mathematica environment, with termination conditions set at 20,000 iterations or solution stabilization, providing practical computational boundaries for the optimization process.

### **Impact on Project Scheduling Effectiveness**

The application of Tabu Search algorithms has yielded substantial quantitative improvements in project scheduling efficiency (Podolski, 2017). The implementation resulted in a remarkable reduction of the total project duration from 534 working days in the baseline scheduling scenario to 264 working days in the optimized schedule, representing a 50.6% improvement in temporal efficiency. This significant compression of execution timelines was achieved without necessitating additional resource allocation, directly enhancing scheduling effectiveness while simultaneously meeting stringent investor deadlines. Podolski (2017) noted that the Tabu Search algorithm proved particularly effective in large-scale, multiunit project environments characterized by complex resource and precedence constraints, conditions where traditional scheduling methods often struggle to produce optimal solutions. The case study involving the construction of 12 petrol stations validated the algorithm's practical utility, with multiple algorithms running consistently outperforming reference solutions.

#### 4.3.5 Classical Machine Learning Models

Classical machine learning models represent a significant category of artificial intelligence techniques applied to project scheduling management. These approaches include the decision trees, random forests, K-nearest neighbors (K-NN), AdaBoost, and process mining algorithms such as Inductive Miner. The reviewed literature demonstrates a notable trend toward ensemble methods, particularly random forest, which achieved superior performance in task allocation prediction compared to single classifiers (Al-Fraihat et al., 2024). Additionally, process mining with Inductive Miner emerged as an effective technique for extracting project models from historical execution data (Cohen, 2024). These studies collectively indicate that supervised learning algorithms predominate in project scheduling applications, likely due to their interpretability and ability to handle labeled historical project data.

##### Implementation in Project Scheduling

Classical machine learning models have been implemented across diverse project contexts, particularly in software development and construction industries. In distributed agile software development environments, multiple supervised learning algorithms were deployed to predict optimal task-role assignments based on textual features extracted from task descriptions (Al-Fraihat et al., 2024). The implementation involved comprehensive data preprocessing, including cleaning, one-hot encoding of categorical labels, normalization, and addressing class imbalance through techniques such as SMOTETomek. The researchers fine-tuned hyperparameters for each algorithm, with random forest configured with 200 estimators and maximum tree depth of 20, K-NN utilizing 10 neighbors with Euclidean distance metrics, decision trees limited to depth 10, and AdaBoost employing 100 weak learners with reduced learning rates.

In construction and information systems development projects, Cohen (2024) implemented process mining using the Inductive Miner algorithm to extract structured project models from historical event logs. This data-driven approach relaxed temporal constraints and decoded project variations to form flexible project plans. The discovered Petri nets were enhanced into Timed Petri nets by associating each transition with specific time durations, enabling more accurate simulation of project execution. Cohen

(2024) further integrated decision tree classifiers to extract interpretable decision rules for selecting among alternative project plan variants. These rules were embedded into the Timed Petri nets by annotating decision points with predicted path selections, creating an explainable and actionable planning framework that captured activities that could be performed in parallel while providing guidance for constraint handling and schedule optimization.

### **Impact on Project Scheduling Effectiveness**

The application of classical machine learning models has demonstrated substantial positive impacts on project scheduling effectiveness across various dimensions. In task allocation prediction, random forest achieved the highest accuracy at 96.7%, followed by K-NN (94.2%), decision trees (93.5%), and AdaBoost (93.0%) (Al-Fraihat et al., 2024). This high-accuracy task-role assignment facilitated improved workforce distribution, enhanced team productivity, and reduced scheduling inefficiencies caused by responsibility misallocation. The interpretability of decision trees provided clear decision paths for task assignment, beneficial for manual auditing, while AdaBoost demonstrated resilience by focusing on difficult-to-predict cases, improving scheduling robustness when dealing with ambiguous tasks.

The process mining approach with Inductive Miner substantially improved project planning by revealing previously hidden flexibility in task sequencing (Cohen, 2024). By relaxing unnecessary precedence constraints, the discovered models enabled shorter project durations and greater resource concurrency. Using enriched Timed Petri nets, the approach allowed critical path recalculations, leading to observed reductions of up to 26% in project duration for real-world datasets. Furthermore, the integration of supervised learning for variation selection automated decisions traditionally based on planner intuition or experience, reducing subjective biases and improving alignment of project schedules with actual project needs. This strengthened the ability to preempt scheduling risks arising from inappropriate plan selections and ensured that resource allocations and task timings were better tailored to each new project's specific characteristics (Cohen, 2024).

#### 4.3.6 Fuzzy Systems

Fuzzy Systems (FS) represent a significant field within Artificial Intelligence that addresses uncertainty, ambiguity, and vagueness inherent in real-world decision-making processes. The reviewed literature reveals a consistent application of Fuzzy Logic (FL) techniques to enhance traditional project scheduling methodologies. Fuzzy Logic fundamentally departs from classical binary logic by allowing partial membership values between 0 and 1, thus facilitating more nuanced modeling of uncertainty in project parameters (Pregina & Kannan, 2024). The analytical review demonstrates an evolution in fuzzy implementations, progressing from basic Fuzzy Logic integration to more sophisticated approaches such as Linear Diophantine Fuzzy Sets (LDFS). Each reviewed study employs distinct fuzzy mathematical formalisms, Trapezoidal Fuzzy Numbers (Pregina & Kannan, 2024), Triangular Fuzzy Numbers and Sigmoid Functions (Pusztai et al., 2019), and Linear Diophantine Fuzzy Numbers (Parimala et al., 2023), tailored to address the specific uncertainties in their respective project scheduling contexts. Notably, these fuzzy techniques are predominantly implemented as hybrid systems, enhancing conventional scheduling methods such as Critical Path Method (CPM), Program Evaluation and Review Technique (PERT), and Graphical Evaluation and Review Technique (GERT).

##### **Implementation in Project Scheduling**

The implementation of Fuzzy Systems in project scheduling manifests primarily through the enhancement of traditional scheduling methodologies across diverse industry contexts. In the construction industry, Pregina & Kannan (2024) integrated Fuzzy Logic with the Graphical Evaluation and Review Technique (GERT) to create Fuzzy-GERT (F-GERT), addressing the inherent uncertainty in construction activity durations. This implementation employed Trapezoidal Fuzzy Numbers (TFNs) to represent imprecise activity durations and utilized the Center of Gravity method for defuzzification, enabling practical decision-making in real-world construction scheduling scenarios. Similarly, within manufacturing contexts, Pusztai et al. (2019) enhanced the Critical Path Method by replacing fixed activity durations with fuzzy values derived through two distinct approaches: Fuzzy Triangular Numbers based on minimum, average, and maximum time measurements, and Sigmoid-shaped fuzzy functions based on cumulative distribution functions. This

implementation utilized MATLAB and Microsoft Excel Solver for computational analysis, fundamentally altering project timing estimates by incorporating operational uncertainties directly into the critical path calculations.

A more advanced implementation was demonstrated by Parimala et al. (2023), who developed Linear Diophantine Fuzzy Set (LDFS) theory applications in both PERT and CPM methodologies (LDF-PERT and LDF-CPM). This approach extended beyond traditional fuzzy implementations by incorporating additional control parameters, satisfaction, dissatisfaction, and reference parameters, allowing for more sophisticated modeling of uncertainty in activity durations. The implementation included specially developed forward and backward pass algorithms adjusted to operate under LDFS principles, with custom aggregation operations and critical path identification methodologies based on fuzzy arithmetic. Parimala et al. (2023) validated this approach through applications in both construction and garment industry projects, demonstrating its versatility across different project types. Across all implementations, the consistent pattern observed is the transformation of deterministic or probabilistic scheduling methods into fuzzy-enhanced systems capable of accommodating the inherent uncertainty and imprecision of real-world project activities.

### **Impact on Project Scheduling Effectiveness**

The integration of Fuzzy Systems into project scheduling methodologies has demonstrated significant improvements in scheduling accuracy, uncertainty management, and overall project control. In terms of quantifiable outcomes, Pregina & Kannan (2024) achieved remarkable accuracy, with estimated project durations 94% proximate to actual completion times for their case study. When validated against forty-five real-world construction projects, F-GERT consistently outperformed conventional methods, maintaining proximity to actual durations of 95% for small projects, 93% for medium projects, and 90% for large projects. This represents a substantial advancement over Critical Path Method, Program Evaluation and Review Technique, and Monte Carlo simulated GERT networks in terms of forecast reliability.

Similar improvements in accuracy were reported by Pusztai et al. (2019), whose fuzzy logic enhancements to CPM improved scheduling accuracy by approximately 7%

compared to traditional CPM based on mean values. Among the approaches that were tested by them, the fuzzy sigmoid function with a  $\gamma$ -value of 0.8 yielded the closest match to real-world production times. This increased accuracy translated into tangible operational benefits, allowing more realistic production planning that better reflected actual capacity (10 machines per week rather than an inaccurate estimate of 12 machines per week), thus reducing the risk of unmet production targets.

While Parimala et al. (2023) did not provide extensive quantitative comparisons, their qualitative analysis highlighted several important impacts: simplified decision-making under uncertainty, more precise modeling of ambiguous time estimates, and the derivation of more resilient critical paths. Their LDF-PERT and LDF-CPM models demonstrated enhanced scheduling accuracy, improved risk mitigation through better accounting for variability in task times, and reduced dependency on dummy activities often required in traditional CPM/PERT implementations.

#### **4.3.7 Reinforcement Learning**

Reinforcement Learning (RL) enables computational agents to learn optimal decision-making policies through environment interaction and reward maximization. This machine learning approach has been applied to project scheduling through Monte Carlo Control (MCC) methods (Szwarcfiter et al., 2023; Szwarcfiter & Herer, 2024) and Deep Q-Networks (DQN) (Cui, 2024), collectively addressing uncertainty in activity durations and project costs. A consistent pattern across studies is the utilization of exploration-exploitation mechanisms to enhance learning in dynamic project environments. Szwarcfiter et al. (2023) demonstrate that RL is particularly suited for dynamic optimization tasks under stochastic conditions, while Cui (2024) highlights its capacity to handle Szwarcfiter & Herer (2024) cases. Szwarcfiter & Herer (2024) further emphasize RL's capability to integrate both time-dependent financial objectives and stakeholder value preferences into scheduling decisions.

#### **Implementation in Project Scheduling**

RL implementations span engineering, construction, and defense sectors with varied approaches. In foundational implementations, project activities are conceptualized as

states while execution modes serve as actions (Szwarcfiter et al., 2023). Szwarcfiter et al. (2023) employed Monte Carlo Control utilizing average reward update and constant step-size update strategies with  $\epsilon$ -greedy policies. Similarly, Szwarcfiter & Herer (2024) implemented MCC to estimate action-value functions based on simulated project completions in construction and defense projects. Their approach incorporated optimistic initial values to encourage diverse plan discovery during the learning process.

Cui (2024) advanced implementation through Deep Q-Networks in engineering projects. This approach featured fully connected layers with 128 hidden nodes and ReLU activation functions. Cui (2024) incorporated a dynamic feedback mechanism adjusting learning rates and exploration rates, with experience replay and target networks enhancing training stability. All implementations formulate project scheduling as sequential decision-making problems where agents optimize activity timing and resource allocation through simulated environment interaction. The implementation by Szwarcfiter & Herer (2024) specifically focused on computing rewards as weighted sums of robust Net Present Value and project value to address financial considerations.

### **Impact on Project Scheduling Effectiveness**

RL methodologies demonstrate measurable advantages over traditional optimization approaches in solution quality and computational efficiency. Comparative analyses reveal consistent performance improvements across multiple studies (Szwarcfiter et al., 2023; Cui, 2024; Szwarcfiter & Herer, 2024). Szwarcfiter et al. (2023) reported RL outperforming Genetic Algorithms in both solution quality and speed for Lean Project Management, while producing shorter project delivery durations than conventional scheduling methods in Critical Chain Buffer Management applications.

Quantitatively, Cui's (2024) DQN implementation achieved convergence after approximately 80 training iterations compared to 180-220 iterations for traditional algorithms. Cui (2024) demonstrated solution generation in 3.04 seconds versus 4.26-5.21 seconds with traditional approaches, translating to economic impact with a reduced project cost of 913,000 yuan. The dynamic feedback mechanism proved essential in maintaining scheduling flexibility and avoiding local optima entrapment.

Szwarcfiter & Herer (2024) demonstrated superior tradeoffs between project value and robust NPV compared to mathematical solvers and Tabu Search, particularly in larger problem instances. Their approach enabled selective delay or advancement of activities based on cash flow characteristics, improving project outcomes under uncertainty. A consistent advantage across studies was RL's capacity to generate efficient frontiers of project plans, providing stakeholders with systematic options for balancing risk, value, and financial returns (Szwarcfiter et al., 2023). Szwarcfiter & Herer (2024) further emphasized this capability as particularly valuable in complex project environments where conventional methods encounter computational limitations.

#### **4.3.8 Generative Pre-trained Transformers**

Generative Pre-Trained Transformers (GPT) represent a significant advancement in Natural Language Processing (NLP) with emerging applications in project scheduling management. These Large Language Models (LLMs) leverage deep learning architectures designed to process sequential data and understand contextual relationships in text. The reviewed literature examines three distinct implementations of GPT models, GPT-J, GPT-3.5, and GPT-4, across different project domains. GPT models demonstrate versatility in project scheduling through their ability to analyze documentation, generate schedules, and provide decision support. These models represent a nascent but rapidly evolving approach to project management, with implementations ranging from fine-tuned domain-specific applications to general-purpose conversational interfaces. Notably, all implementations maintain human oversight while automating traditionally manual scheduling processes.

##### **Implementation in Project Scheduling**

The implementation of GPT models in project scheduling spans diverse industries with varying levels of specialization and integration. In software development projects, a transformer-based AI-Analyst framework utilizing a modified GPT-J architecture comprising over 150 million parameters across 12 encoder layers was implemented (Faruqui et al., 2024). This implementation employed transfer learning techniques, where the base model underwent fine-tuning with domain-specific Software Development Life Cycle

(SDLC) documentation. Faruqui et al. (2024) operationalized the framework through a three-module system for analyzing project documents, optimizing resource allocation, identifying inefficiencies, and recommending risk mitigation strategies. In the construction industry, ChatGPT (based on GPT-3.5) was applied to generate construction schedules from natural language project descriptions (Prieto et al., 2023). Prieto et al. (2023) demonstrated how this implementation extracted tasks, identified dependencies, estimated resources, and predicted durations for construction activities without additional fine-tuning beyond OpenAI's standard model. For digital technology sector projects, GPT-4 was employed to autonomously generate comprehensive project plans adhering to PMI's PMBOK Guide standards (Barcaui & Monat, 2023). Barcaui & Monat (2023) utilized structured prompt engineering across approximately 15 iterative dialogue rounds to refine artifacts covering key knowledge areas including scope, schedule, cost, and risk management. All three implementations demonstrate how GPT models can be adapted for project scheduling through different approaches, specialized fine-tuning (Faruqui et al., 2024), direct application of generalized models (Prieto et al., 2023), or sophisticated prompt engineering (Barcaui & Monat, 2023).

### **Impact on Project Scheduling Effectiveness**

The integration of GPT models has yielded measurable impacts on project scheduling effectiveness, though with notable limitations requiring human oversight. The most substantial quantitative improvements were reported with the GPT-J-based framework achieving over 91% F1-score in task prioritization and classification, alongside a 53.33% reduction in business costs attributed to improved efficiency (Faruqui et al., 2024). Faruqui et al. (2024) also demonstrated remarkable performance in reducing inference time to approximately 120 milliseconds per scheduling decision, enabling near real-time adjustments. In contrast, while ChatGPT generated logical construction schedules within seconds, qualitative limitations emerged, including the introduction of erroneous tasks that are not present in project scopes and inconsistent reliability for professional-grade scheduling (Prieto et al., 2023). Similarly, Barcaui & Monat (2023) observed that GPT-4 produced schedules rapidly but with less granularity compared to human project managers, the AI generated 25 high-level activities over a 12-month timeline, whereas

human planners developed 175 detailed activities spanning 15 months. Barcaui & Monat (2023) noted GPT-4's strengths in standardized formatting and risk identification but identified weaknesses in detailed resource management and dependency modeling. Collectively, these studies indicate that GPT models significantly expedite initial scheduling processes but currently complement rather than replace human expertise, particularly for complex project environments requiring nuanced contextual understanding (Barcaui & Monat, 2023).

#### **4.4 Hybrid-Method AI System Implementation and Impact**

Hybrid-Method AI Systems in this review represent approaches that integrate techniques from two or more distinct AI fields. These systems intentionally combine diverse methodologies, such as coupling Evolutionary Algorithms (EA) with Neural Networks (NN) or merging Swarm Intelligence (SI) with Optimization and Metaheuristics (OM), to achieve synergistic improvements. Recent trends aim to integrate these different components to take advantage of complementary features and to develop synergistic systems leading to hybrid architecture such as neuro-fuzzy systems. By leveraging multiple AI categories, hybrid systems seek to address complex project scheduling challenges more effectively than any single-method approach could. Their inclusion highlights the growing trend toward interdisciplinary AI solutions that aim for greater flexibility, scalability, and robustness.

##### **4.4.1 Evolutionary Algorithm**

Evolutionary Algorithms (EAs) represent a significant subset of artificial intelligence techniques applied to project scheduling management, drawing inspiration from biological evolution principles such as selection, reproduction, and mutation. The literature reveals extensive application of these algorithms, particularly Genetic Algorithms (GAs), which appeared in 13 of the 15 reviewed studies. Other evolutionary techniques include Differential Evolution (DE) implemented in three studies (Aristotelous & Nearchou, 2024; Cheng & Tran, 2016; Cheng et al., 2017) and the Strength Pareto Evolutionary Algorithm II (SPEA2) appearing in one study (Hussain et al., 2024). These hybridizations spanned multiple AI domains: Neural Networks (Bakhshi et al., 2022; Zeng & Gao, 2024), where

GAs optimized neural network parameters for project forecasting; Swarm Intelligence, with Particle Swarm Optimization hybridization appearing in multiple studies (Aristotelous & Nearchou, 2024; Akhbari, 2022); Fuzzy Systems, where fuzzy logic combined with GAs enhanced subcontractor prioritization (Zeng & Gao, 2024); and Agent-Based Systems, where GAs operated within multi-agent frameworks to coordinate resource allocation across project portfolios (He et al., 2022; Khanzadi et al., 2016). Additionally, hybridization with Optimization and Metaheuristics field was prominent, incorporating techniques like Simulated Annealing (Aminbakhsha & Ahmed, 2024), Hill Climbing (Ge & Xu, 2016), and various local search heuristics (Aristotelous & Nearchou, 2024; Aquino et al., 2022). This systematic integration of Evolutionary Algorithms with complementary AI fields suggests that while EAs provide powerful global search capabilities for complex scheduling problems, they benefit significantly from specialized components that address specific limitations in local refinement, constraint handling, or predictive modeling. The predominance of GAs across hybrid systems demonstrates their adaptability as optimization engines within diverse architectural frameworks, while specialized evolutionary approaches like chaos-enhanced DE offer targeted solutions for avoiding premature convergence in specific scheduling contexts.

### **Implementation in Project Scheduling**

The implementation of evolutionary algorithms spans diverse industries, with construction appearing most frequently (seven studies), followed by software development (three studies), and information systems (one study), while four studies did not specify their industry context. Genetic Algorithms were primarily set up through specialized "chromosome" representations, essentially, encoded solutions that represent different scheduling options such as task orders, resource assignments, and execution methods. In construction projects, these representations took various forms: floating-point numbers (Aristotelous & Nearchou, 2024) (Aristotelous & Nearchou, 2024), genes representing different ways to execute activities (Aminbakhsha & Ahmed, 2024), and values representing possible delays for non-critical activities (Iranagh et al., 2023). Within Iranagh et al.'s (2023) approach, the GA served as the main search component in a broader Memetic Algorithm framework, where potential solutions were encoded as

numerical values between 0 and 1. The process for selecting promising solutions varied across studies, with some using tournament selection, where small groups of solutions compete (Aquino et al., 2022; Li & Xu, 2018), roulette wheel selection, where better solutions have higher chances of selection (Akhbari, 2022; Iranagh et al., 2023), or keeping the best solutions from generation to generation through "elitist" approaches (Koszyán et al., 2022). In Koszyán et al.'s (2022) implementation, they combined both binary (yes/no) components and numerical values, incorporating employee relationships and team dynamics through specialized matrices and network analysis, and further refined solutions using a mathematical technique called Nelder-Mead minimization. The way solutions were combined or "crossed over" was typically customized to maintain the logical order of tasks, with two-point crossover, where parts of two solutions are exchanged, appearing frequently (Aquino et al., 2022; Akhbari, 2022; Zhao et al., 2024).

A related approach called Differential Evolution showed interesting adaptations for project scheduling challenges. Cheng & Tran (2016) enhanced the standard method with "chaotic mapping", using mathematical patterns that appear random but follow deterministic rules, to help avoid getting stuck in suboptimal solutions when scheduling projects with limited resources. Similarly, Cheng et al. (2017) developed a variation that adjusted task start times within their available flexibility windows using these chaotic patterns instead of purely random values, helping to explore more diverse scheduling possibilities. Aristotelous & Nearchou (2024) implemented Differential Evolution with a specific mathematical formula (the "best/1/bin" strategy) and precise control parameters ( $F=0.5$ ,  $CR=0.6$ ) to address resource leveling in construction projects, and combined it with local search methods (LS1, LS2) and other algorithms like Genetic Algorithms and Particle Swarm Optimization in a sequential approach. Khazadi et al. (2016) set up their Genetic Algorithm to work within a broader system where first task durations were predicted using Support Vector Regression, then incorporated into the traditional Critical Path Method, with each solution representing different worker assignment options and selecting solutions through a technique called Stochastic Universal Sampling as part of an Agent-Based Modeling approach.

The combination or "hybridization" of different techniques emerged as a common implementation strategy. Some notable combinations included: Genetic Algorithms with neural networks and filtering techniques to predict project times and costs (Bakhshi et al., 2022); Genetic Algorithms with neural networks, fuzzy logic, and auction-based systems for matching tasks with workers and distributing resources (Zeng & Gao, 2024); Genetic Algorithms with a local search technique called Hill Climbing to fine-tune schedules (Ge & Xu, 2016); and Genetic Algorithms with Simulated Annealing, a technique inspired by metallurgy, to improve the search for optimal solutions (Aminbakhsha & Ahmed, 2024).

Many implementations focused on balancing multiple competing objectives simultaneously. The NSGA-II variant of Genetic Algorithms was used to both minimize project duration and distribute workload fairly among team members in internet research projects by matching tasks to workers based on their skills and spreading out the assignments evenly (Zhao et al., 2024). Similarly, the Strength Pareto Evolutionary Algorithm II (SPEA2) was set up with specialized crossover operations that maintained task dependencies and a two-stage mutation process to optimize both financial returns (net present value) and environmental impact (greenhouse gas emissions) in construction projects (Hussain et al., 2024). This approach was implemented alongside the Modified Grey Wolf Optimizer for comparison purposes. Aquino et al. (2022) implemented Genetic Algorithms in parallel with several other methods, Greedy Search (which makes the best immediate choice at each step), Cosine Pigeon-Inspired Optimizer (based on pigeon navigation behavior), and Iterated Local Search (which repeatedly makes small improvements), for assigning staff to tasks in information systems projects, using a binary coding system to represent employee-task assignments and considering task sharing scenarios.

Several studies have developed complex frameworks integrating multiple techniques. He et al. (2022) created a multi-level system where Genetic Algorithms functioned at the strategic planning level to determine both the sequence of projects and how resources should be distributed among them, while Ant Colony Optimization (inspired by ant foraging behavior) handled the scheduling of individual projects. F. Li & Xu (2018) implemented Genetic Algorithms with a two-stage scheduling approach: first assigning the

earliest possible start times to activities (forward scheduling), then adjusting these times based on available slack (backward scheduling) to create more compact schedules. Akhbari (2022) used Genetic Algorithms in two distinct ways: as an "outside" search method for determining activity sequences and execution modes in combination with nature-inspired techniques like Cuckoo Optimization Algorithm, Grey Wolf Optimizer, and Particle Swarm Optimization; and as an "inside" search method across all models for optimizing material ordering plans.

### **Impact on Project Scheduling Effectiveness**

The application of evolutionary algorithms delivered significant improvements across several key performance areas in project scheduling. Regarding resource management, these techniques consistently enhanced allocation efficiency and smoothed resource usage patterns. Multiple studies demonstrated measurable resource optimization: Zhao et al. (2024) achieved a substantial 40% reduction in overall resource consumption while enabling projects to complete within more predictable timeframes (45-55 days); Aristotelous & Nearchou (2024) reduced resource usage fluctuations significantly as measured by the resource deviation metric; and Cheng et al. (2017) lowered peak manpower requirements and minimized variations between consecutive time periods. These resource improvements translated directly into financial benefits. Khanzadi et al. (2016) documented approximately 20% project cost reduction through optimized labor resource allocation while Aminbakhsha & Ahmed (2024) demonstrated improvements in project financial returns. Zeng & Gao (2024) showed that better optimization of task-worker matching led to more reliable schedules with reduced risk of bottlenecks and idle time, providing project managers with more dependable forecasts for resource requirements and completion dates.

Improvements in project duration management represented another significant benefit area. These algorithms excelled at finding balanced solutions for the classic time-cost trade-off problem that challenges many project managers. F. Li & Xu (2018) demonstrated impressively accurate schedules, achieving less than 1% deviation from theoretical optimal solutions across an extensive dataset of 1,295 project scenarios while maintaining reasonable computation times. He et al. (2022) found that their approach

consistently produced near-optimal project plans with minimal variation in expected delays, providing more predictable outcomes for portfolio management. Iranagh et al. (2023) showed how these techniques could identify scheduling options that maintained project durations while significantly improving resource distribution, avoiding the resource peaks and valleys that typically plague project execution. Several researchers highlighted the algorithms' ability to create feasible schedules that satisfied all project constraints while remaining compact and efficient (Ge & Xu, 2016; Aminbakhsha & Ahmed, 2024). A particularly valuable benefit was improved prediction capability, with Bakhshi et al. (2022) demonstrating how these techniques could provide early warnings about potential delays and cost overruns, enabling project managers to take preventive action rather than reactive measures. This predictive advantage was especially beneficial in construction projects, where Aminbakhsha & Ahmed (2024) showed that evolutionary techniques could help managers schedule overlapping activities appropriately and select execution methods that balanced cost and time constraints while meeting contractual deadlines.

Comparative analysis across studies revealed important performance insights about these techniques in different contexts. While evolutionary algorithms demonstrated broad applicability, their performance varied depending on implementation specifics and problem characteristics. Some studies identified limitations that project managers should consider. Aquino et al. (2022) found that while these algorithms provided good solutions for staff allocation in information systems projects, they were generally outperformed by another technique called Iterated Local Search in terms of solution quality, though they still offered significant improvement over simpler approaches like random assignment or greedy algorithms. Similarly, Hussain et al. (2024) reported that their SPEA2 implementation, while valid, didn't perform as well as the Modified Grey Wolf Optimizer when balancing economic and environmental objectives, although it did complete its calculations faster, an important consideration for time-sensitive planning scenarios. Akhbari (2022) observed that when used as a standalone approach for high-level scheduling decisions, evolutionary algorithms showed inferior performance compared to other nature-inspired methods (specifically Cuckoo Optimization and Grey Wolf

Optimizer), yet performed effectively when applied to material ordering optimization, suggesting they may be better suited for certain types of scheduling sub-problems. Kosztyán et al. (2022) demonstrated a particularly valuable capability: the ability to account for team dynamics and interpersonal relationships when scheduling activities, reducing project durations and costs in scenarios where team members worked well together, a human factor often overlooked in traditional scheduling approaches.

The adaptability of evolutionary algorithms in handling complex, real-world constraints emerged as their most significant contribution to project scheduling practice. Ge & Xu (2016) demonstrated how these techniques could find cost-effective project plans faster than experienced human planners while adapting to changes that inevitably occur during project execution, reducing overall costs and improving how effectively resources were used. The enhanced problem-solving capabilities resulted in more stable and accurate schedules, as shown by both Cheng & Tran (2016) and Cheng et al. (2017), whose approaches achieved higher success rates and less variability in outcomes compared to conventional methods. Cheng & Tran (2016) particularly showed improvements in both reliability (consistency of results) and efficiency (quality of solutions) for optimal scheduling decisions.

These advantages were especially evident in construction projects with intricate task dependencies, where Aminbakhsha & Ahmed (2024) showed how evolutionary techniques could handle real-world complexities like overlapping activities and variable construction methods that traditional scheduling approaches struggle with. Perhaps most significantly for modern project management challenges, these algorithms demonstrated an ability to balance multiple competing objectives simultaneously (Zhao et al., 2024; Hussain et al., 2024), providing project managers with optimized solutions that considered trade-offs between factors such as time, cost, resource levels, and even environmental impacts. This multi-objective capability represents a substantial advancement over traditional scheduling approaches that typically optimize for a single factor like time or cost, offering project managers more comprehensive decision support that reflects the true complexity of today's project environments.

#### 4.4.2 Neural Network

Neural Networks represent a predominant artificial intelligence technique employed in project scheduling management, encompassing various architectural variants including Multilayer Perceptron (MLP), Artificial Neural Networks (ANN), Backpropagation Neural Networks (BP-NN), Radial Basis Function Neural Networks (RBF NN), Convolutional Neural Networks (CNN), Graph Convolutional Neural Networks (GCNN), and Doc2Vec. The reviewed literature demonstrates neural networks' significant application across scheduling tasks, frequently implemented as standalone predictive models or hybridized with optimization algorithms and other analytical frameworks. Notably, several researchers (Bakhshi et al., 2022; Bugayenko et al., 2023) adopted hybrid approaches combining neural networks with metaheuristic optimization techniques such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) to enhance performance. The architectural diversity reflects task-specific adaptations, with simpler MLP and ANN structures prevalent in standard prediction scenarios (Yu et al., 2021; Zhang & Li, 2024) and advanced CNN and GCNN architectures deployed for complex relational scheduling problems (Wang, 2022; Yao et al., 2024).

##### Implementation in Project Scheduling

Neural network implementations in project scheduling predominantly occur within construction industry contexts, with occasional applications in software development projects. The fundamental implementation approach involves utilizing neural networks as predictive engines for critical scheduling parameters. In construction projects, several researchers implemented neural networks to predict schedule performance indicators, particularly focusing on earned value metrics and completion timeframes. F. Yu et al. (2021) implemented Backpropagation Neural Networks (BP-NN) as a forecasting engine for future schedule performance based on planned resource inputs, using quasi-Newton optimization for network training. Bakhshi et al. (2022) specifically utilized MLP neural networks hybridized with Genetic Algorithms and Particle Swarm Optimization to predict project duration and cost using earned schedule (ES), earned value (EV), actual progress (AP), and actual cost (AC) indicators from dam construction project data. Similarly, Soetjpto et al. (2024) developed a hybrid system integrating Earned Value Management with

Artificial Neural Networks (EVM-ANN) that incorporated dynamic project conditions including equipment usage, material logistics, and environmental factors to predict Schedule Performance Index values.

Construction resource allocation scenarios represented another significant implementation domain. Zeng & Gao (2024) applied neural networks to predict subcontractors' future execution costs and potential delays, with these predictions feeding into fuzzy logic and auction-based resource allocation systems. In parallel, Yu & Zuo (2022) implemented deep neural networks within a deep reinforcement learning framework for optimizing construction task sequencing, employing convolutional neural network (CNN) structures to represent construction states and estimate Q-values for scheduling action selection. More specialized neural network variants were implemented for specific scheduling challenges, including Wang's (2022) CNN application within a deep reinforcement learning framework for extracting features from resource states and job queues, and Yao et al.'s (2024) GCNN implementation for modeling complex precedence constraints in construction projects as graph structures. For text-based task prioritization in software development contexts, Bugayenko et al. (2023) implemented Doc2Vec neural networks to vectorize task descriptions from GitHub repositories, which were subsequently utilized within a PSO-optimized linear model for backlog prioritization. Zhang & Li (2024) implemented an Artificial Neural Network with one hidden layer of 50 neurons to predict construction duration for individual work areas, while Hajali-Mohamad et al. (2016) applied Radial Basis Function Neural Networks to estimate earned value curves from plan value data. Liben et al. (2024) implemented a basic ANN model for construction duration prediction, though with less sophisticated architectural design than counterparts.

### **Impact on Project Scheduling Effectiveness**

Neural networks demonstrated substantive positive impacts on project scheduling effectiveness across multiple performance dimensions. In predictive accuracy, the implementation of neural networks consistently outperformed traditional scheduling methods. Bakhshi et al.'s (2022) hybrid MLP models generated early warning signals for schedule delays well before conventional earned value-based forecasts, enabling preemptive corrective actions during initial project stages. Similar predictive advantages were

documented by Hajali-Mohamad et al. (2016), whose Radial Basis Function Neural Network (RBF NN) achieved remarkably low Mean Absolute Percentage Error (MAPE) of 0.34% in earned value forecasting. F. Yu et al. (2021) reported that BP-NN integration reduced MAPE to 5.68%, outperforming traditional methods' 8.36% error rate – a 32.06% relative improvement in schedule forecasting accuracy.

The implementation impact extended beyond predictive accuracy to scheduling optimization outcomes. X. Yu and Zuo's (2022) deep neural network implementation within a deep reinforcement learning framework reduced construction periods from 57 days (traditional method) to 55 days, while simultaneously decreasing computational overhead and enhancing adaptability to changing site conditions. Yao et al. (2024) found that GCNN-based implementations converged 25-30% faster than MLP counterparts, demonstrating superior feature extraction capabilities for complex projects with hierarchical constraints. Similarly, Wang's (2022) CNN-enhanced scheduling agent within a deep reinforcement learning architecture detected subtle resource allocation patterns that manual approaches typically missed, enabling more efficient multi-project resource scheduling. Zeng & Gao (2024) demonstrated that their Artificial Neural Networks (ANNs) achieved strong performance metrics (Mean Absolute Error [MAE] = 18.88; Root Mean Square Error [RMSE] = 22.98) in predicting subcontractor delays, reducing task bottlenecks through proactive resource distribution.

Bugayenko et al. (2023) showed that Doc2Vec neural embeddings significantly enriched the feature representation of software development tasks, leading to more contextually appropriate scheduling recommendations. Zhang & Li (2024) reported that their ANN model outperformed alternatives with superior validation results (MAE of 2.495, RMSE of 3.796, and coefficient of determination [ $R^2$ ] of 0.944) for work-area level construction duration prediction.

However, neural network implementations were not universally successful. Liben et al. (2024) reported that their ANN implementation failed to improve project scheduling efficiency, achieving negligible coefficient of determination ( $R^2$ ) values (0.00) and high RMSE (495 days), underscoring the critical importance of sufficient high-quality training data for neural network effectiveness. This contrasted with Soetjipto et al.'s (2024)

comprehensive EVM-ANN hybrid, which achieved 94.46% prediction accuracy compared to standalone EVM (86.16%) and ANN (92.72%) implementations, demonstrating the particular value of hybrid approaches that dynamically incorporate changing project conditions into neural network forecasts.

#### **4.4.3 Swarm Intelligence**

Swarm Intelligence (SI) represents a significant branch of artificial intelligence employed in project scheduling optimization. This computational approach models the collective behavior of decentralized, self-organized systems found in nature, such as bird flocks, ant colonies, and wolf packs. The literature review identified several prominent SI techniques applied to project scheduling: Particle Swarm Optimization (PSO) appeared in six studies (Bakhshi et al., 2022; Aristotelous & Nearchou, 2024; Akhbari, 2022; Bugayenko et al., 2023; Wei et al., 2023), followed by Ant Colony Optimization (ACO) in two studies (He et al., 2022; Zhao et al., 2024), Grey Wolf Optimization (GWO) in two studies (Hussain et al., 2024; Akhbari, 2022), and specialized variants including Cosine Pigeon-Inspired Optimizer (CPIO) (Aquino et al., 2022) and Coyote Optimization Algorithm (COA) (Akhbari, 2022). These techniques frequently appeared in hybrid implementations alongside other AI methodologies, particularly genetic algorithms, to leverage complementary strengths in exploration and exploitation of the solution space.

#### **Implementation in Project Scheduling**

Swarm intelligence techniques have been implemented across diverse project environments with various scheduling objectives. In construction projects, PSO was employed to optimize artificial neural network weights for improved project duration and cost forecasting (Bakhshi et al., 2022). This MLP-PSO hybrid adjusted forecasting models dynamically as new project data became available, reducing dependency on manual rescheduling processes. Similarly, Hussain et al. (2024) applied a Multi-objective Grey Wolf Optimization (MGWO) algorithm to balance conflicting objectives in construction projects, specifically maximizing net present value while minimizing greenhouse gas emissions under various resource constraints. The MGWO implementation utilized a solution

encoding that consisted of task execution order and mode assignment lists, enhanced with mutation-based local search and crossover operations.

(Aristotelous & Nearchou, 2024) implemented PSO with floating-point vectors encoding job priorities for scheduling in construction projects, with particles updating positions based on cognitive and social coefficients. Their approach hybridized PSO with greedy heuristics (LS1 and LS2) to smooth resource consumption profiles, while also creating parallel hybrid structures where PSO operated simultaneously with genetic algorithms. For multi-mode resource-constrained project scheduling problems (MRCPSP), Akhbari (2022) implemented three distinct SI techniques (COA, GWO, and PSO) as "outside search" components within a two-tier hybrid optimization framework, each paired with a genetic algorithm handling "inside search" for material ordering decisions. The parameters for these SI techniques were fine-tuned using the Taguchi method to improve robustness.

In software development contexts, Bugayenko et al. (2023) utilized PSO to optimize a linear model for task prioritization across backlogs. The implementation searched for a 31-dimensional parameter space using 200 particles across 39 iterations to optimize weights for minimizing normalized Kendall distance between predicted and actual task sequences. For information system projects, Aquino et al. (2022) implemented CPIO by representing human resource allocations as binary vectors, employing two operational phases: Map and Compass (using cosine similarity to adjust solution trajectories) and Landmark (using solution centrality for refinement). Furthermore, in highway construction projects, Wei et al. (2023) implemented PSO to optimize the initialization of the Harmony Memory database within a Harmony Search algorithm, enhancing the distribution and directionality of initial solutions for multi-objective optimization of construction progress, investment cost, highway quality, and environmental impact.

In multi-project environments, He et al. (2022) implemented ACO within a multi-agent architecture where each Project Agent independently ran an ACO instance to optimize local project schedules after global resource allocations were set by a genetic algorithm. This implementation integrated dynamic heuristic rules adapted to multi-project environments, including activity selection based on earliest possible start times and mode

selection based on earliest finishing times under dynamically available resource capacities. Similarly, Zhao et al. (2024) applied ACO as an auxiliary technique for initial task-to-worker assignment in internet research and development projects, creating preliminary schedules by favoring worker-task combinations promising the shortest completion times.

### **Impact on Project Scheduling Effectiveness**

The implementation of swarm intelligence techniques demonstrated significant positive impacts on project scheduling effectiveness across multiple dimensions. In forecasting applications, the MLP-PSO hybrid model delivered the highest accuracy in predicting project duration and final cost among tested methods, generating early warnings at much earlier stages than traditional forecasting approaches, which substantially enhanced schedule control and reduced risks of project overruns (Bakhshi et al., 2022). For multi-objective optimization scenarios, MGWO significantly improved project scheduling by discovering diverse, high-quality Pareto optimal solutions, providing project managers with broader choice between cost-efficiency and sustainability compared to alternative algorithms (Hussain et al., 2024).

(Aristotelous & Nearchou, 2024) reported that PSO contributed significantly to improving project scheduling by reducing resource fluctuations and enhancing solution diversity. Within parallel hybrid structures, PSO enabled better exploration of solution spaces, resulting in lower DEV values (resource smoothness) and acceptable project durations across large and complex scheduling benchmarks. In comparative analyses against commercial tools, hybrids involving PSO demonstrated superior performance in producing resource-leveled schedules in both synthetic and real-world datasets. For material procurement-integrated scheduling problems, Akhbari (2022) found that among all tested hybrid algorithms, the COA-GA hybrid delivered the best performance across multiple problem sets in terms of relative deviation percentage from optimal solutions, with GWO-GA showing strong results but PSO-GA demonstrating weaker performance, particularly in complex instances with many activities and resource types. In the context of software development, PSO-optimized models achieved significant improvements in backlog prioritization compared to previous machine learning methods, demonstrating

superior task execution sequence predictions and optimizing backlog management (Bugayenko et al., 2023).

ACO implementations showed mixed results across studies. He et al. (2022) reported that ACO significantly enhanced operational-level scheduling by dynamically generating feasible and efficient project schedules respecting time-constrained resource availability, achieving comparable or slightly inferior performance to the best existing heuristics requiring preprocessing, but with much better adaptability to changing conditions. Similarly, Zhao et al. (2024) found that ACO improved the overall efficiency of project scheduling by generating more coherent and feasible initial assignments, accelerating convergence and reducing total project durations.

However, not all swarm intelligence approaches demonstrated uniform effectiveness. The CPIO showed poor performance relative to other heuristics in project scheduling optimization, particularly in larger instances, often struggling to escape local optima (Aquino et al., 2022). This indicates that technique selection must be carefully matched to problem characteristics to achieve optimal results. In highway construction applications, the hybrid PSO-Harmony Search approach led to substantial practical benefits, including 39% advancement in construction schedules, 17% cost savings, and improvements in quality and ecological indices compared to original management plans (Wei et al., 2023). These quantifiable impacts demonstrate the practical value of swarm intelligence techniques in addressing real-world project scheduling challenges.

#### **4.4.4 Optimization and Metaheuristic**

Optimization and metaheuristic techniques represent a prominent class of artificial intelligence approaches utilized in project scheduling management. The analyzed literature reveals diverse applications of these techniques, including Greedy Search, Iterated Local Search, Simulated Annealing, Hill Climbing, Nelder-Mead Method, Harmony Search, Subset Simulation, and Golden Section Search. These methods are frequently implemented as components of hybrid systems, often complementing evolutionary algorithms, machine learning models, or other optimization techniques.

Notably, Simulated Annealing emerged as the most frequently applied technique across multiple studies (Iranagh et al., 2023; Aminbakhsha & Ahmed, 2024; ForouzeshNejad et

al., 2024; Sklias et al., 2024), suggesting its particular suitability for project scheduling optimization challenges. The collective implementation of these techniques demonstrates their adaptability to different project contexts and scheduling requirements, from simple local search refinements to sophisticated probabilistic optimization strategies.

### **Implementation in Project Scheduling**

The implementation of optimization and metaheuristic techniques spans diverse project industries, with predominant applications in construction and software development contexts. In construction project scheduling, Simulated Annealing was implemented within resource leveling frameworks to minimize fluctuations in resource demand (Iranagh et al., 2023). This implementation integrated SA into mutation phases of genetic algorithms, using a Boltzmann probability function to determine acceptance of inferior solutions based on a decreasing temperature parameter. Similarly, in another construction-focused study, Aminbakhsha & Ahmed (2024) applied SA within a hybridized genetic algorithm framework for schedule optimization, systematically regulating the acceptance of worse schedule mutations to avoid entrapment in local optima while determining optimal time-cost combinations and activity sequencing.

The application of metaheuristic techniques in information systems project scheduling is exemplified by Aquino et al. (2022), who implemented both Greedy Search and Iterated Local Search to optimize human resource allocation. Their GS implementation utilized an iterative approach that progressively assigned employees to projects based on immediate improvements to a penalty-based fitness function, while their ILS implementation built upon greedy-initialized solutions by applying one-flip neighborhood searches and randomized perturbations to effectively explore the solution space. In software development projects, Ge & Xu (2016) implemented Hill Climbing as a complementary technique following genetic algorithm optimization, focusing on incremental refinement by mutating single genes representing task assignments or priorities and retaining improvements to enhance schedule fitness.

More specialized implementation approaches include the Nelder-Mead Method applied to software development scheduling by Kosztyán et al. (2022), which refined mixed discrete-continuous solutions by optimizing resource allocation matrices and scheduled

start times, operating over solution structures built using Synergy Mapping Models. For highway construction projects, Wei et al. (2023) implemented Harmony Search algorithm after Particle Swarm Optimization initialization, utilizing memory consideration and pitch adjustment processes for iterative multi-objective schedule optimization. In probabilistic construction scheduling analysis, Zhang & Wang (2021) implemented Subset Simulation to transform rare event probability estimation into a sequence of more frequent intermediate problems, accelerating estimation of project delay probabilities by systematically reducing computational effort through conditional sample generation via Markov Chain Monte Carlo methods.

Advanced decision support implementations include ForouzeshNejad et al. (2024) applying Simulated Annealing to optimize hyperparameters within XGBoost models for project time and cost prediction, and Jakubczyk-Galczyńska et al. (2024) implementing Golden Section Search for time optimization in construction schedule harmonization, iteratively narrowing search intervals based on the golden ratio to identify optimal task durations, time buffers, and critical path interventions. In IT infrastructure projects, Sklias et al. (2024) implemented Simulated Annealing through the Dual Annealing algorithm within a global optimization scheme to adjust project calendars before execution, systematically optimizing task start dates to maximize overlap with specified optimal periods through a custom-designed scoring function.

### **Impact on Project Scheduling Effectiveness**

The implementation of optimization and metaheuristic techniques demonstrated significant impacts on project scheduling effectiveness across multiple dimensions. Iterated Local Search consistently outperformed other heuristics in human resource scheduling optimization, achieving superior allocation solutions across various project scales while adhering to budget constraints (Aquino et al., 2022). This contrasted with Greedy Search, which provided computationally efficient but less optimal solutions, highlighting the trade-off between solution quality and computational expense. The integration of Simulated Annealing into genetic algorithm frameworks substantially enhanced scheduling robustness and convergence quality, allowing systems to escape poor local optima

during early search stages and fine-tune during later stages, resulting in improved resource leveling outcomes (Iranagh et al., 2023).

Local search techniques demonstrated precise optimization benefits when applied to specific scheduling constraints. The shifting heuristic implemented by Iranagh et al. (2023) substantially enhanced optimization by locally smoothing resource profiles beyond global search achievements, while Hill Climbing accelerated convergence toward high-quality solutions and significantly reduced computation time compared to standalone genetic algorithms (Ge & Xu, 2016). Similarly, the Nelder-Mead Method improved solution quality after genetic algorithm phases, leading to additional reductions in project costs and improved schedule compactness (Koszyán et al., 2022).

Quantitative impacts were particularly notable in certain implementations. The XGBoost-SA model achieved over 92% accuracy in project forecasting, reducing cost prediction errors by approximately 50% and time prediction errors by around 80% compared to baseline methods (ForouzeshNejad et al., 2024). Subset Simulation reduced computational time by an order of magnitude while maintaining precise failure probability estimations (Zhang & Wang, 2021), while Golden Section Search application allowed reduction of project workdays from 8 to 6 while establishing a harmonized 24% time buffer (Jakubczyk-Galczyńska et al., 2024).

The SA-based GA implemented by Aminbakhsha & Ahmed (2024) demonstrated substantial enhancement in schedule optimization robustness and convergence quality, enabling faster convergence to high-quality solutions for complex real-world construction projects. Sklias et al. (2024) reported that applying Simulated Annealing through global calendar optimization produced substantial improvements in project scheduling alignment, shifting task dates by between 66 and 121 days compared to original plans, enhancing project resilience and efficiency. In multi-objective optimization, Harmony Search enabled better convergence on the Pareto front and high stability, resulting in significant reductions in project duration and cost (Wei et al., 2023).

Collectively, these impacts reveal that optimization and metaheuristic techniques offer substantial value to project scheduling through enhanced computational efficiency, improved solution quality, reduced project durations, and more reliable cost estimations.

The techniques demonstrate particular effectiveness when implemented within hybrid frameworks that leverage their specific strengths while addressing their individual limitations through complementary approaches.

#### **4.4.5 Classical Machine Learning Models**

Classical machine learning models constitute a significant proportion of artificial intelligence applications in project scheduling management, employed either independently or in hybrid configurations with other techniques. These approaches encompass a diverse array of algorithms including regression-based methods such as Support Vector Regression (SVR) (Khanzadi et al., 2016; Zhang & Li, 2024), tree-based ensemble techniques like Random Forest (RF) and Gradient Boosting Trees (GBT) (Liben et al., 2024; Zhang & Li, 2024), and instance-based learning approaches such as k-Nearest Neighbors (KNN) (Liben et al., 2024; Zhang & Li, 2024). Notable implementations also include specialized time-series forecasting algorithms such as Silverkite (Sklias et al., 2024) and advanced ensemble methods like Extreme Gradient Boosting (XGBoost) (ForouzeshNejad et al., 2024). Across the reviewed literature, construction industry projects emerge as the predominant application domain, with these models typically serving predictive functions to enhance schedule optimization through improved duration estimation and resource allocation.

#### **Implementation in Project Scheduling**

Regression-based techniques demonstrate diverse implementation strategies. Khanzadi et al. (2016) configured Support Vector Regression within an Agent-Based Modeling framework, training it on datasets containing worker characteristics, task properties, and management conditions to predict activity durations. Zhang & Li (2024) implemented SVR with optimized parameters to forecast construction timeframes, using systematic validation techniques to ensure prediction quality. Bugayenko et al. (2023) deployed a linear regression model optimized using Particle Swarm Optimization for software development task prioritization, processing features extracted from project backlogs including code characteristics and text descriptions.

Tree-based methods show practical applications across construction projects. Liben et al. (2024) implemented Random Forest models with validation procedures to predict project completion times based on building characteristics and project status. The same researchers also developed Classification and Regression Trees models to create decision rules for duration prediction. Zhang & Li (2024) configured Gradient Boosting Trees with optimized learning parameters to balance prediction accuracy and computational efficiency. ForouzeshNejad et al. (2024) developed an XGBoost implementation processing comprehensive project features including activity counts, uncertainty factors, and resource allocation to predict project time and cost outcomes.

Instance-based learning appears in multiple implementations. Zhang & Li (2024) employed k-Nearest Neighbors regression with standardized feature sets for construction duration forecasting. Liben et al. (2024) implemented KNN with appropriate data preparation techniques alongside Support Vector Machine models designed to capture complex relationships among project features.

Several specialized implementations address specific scheduling challenges. Sklias et al. (2024) deployed the Silverkite algorithm after evaluating multiple forecasting alternatives, configuring it to produce medium-term forecasts for market-sensitive variables like material prices. Zhang & Wang (2021) developed a method using mathematical optimization to automatically estimate project task duration ranges from ongoing progress data, allowing for continuous updates to schedule estimates. Mazzetto (2024) integrated various machine learning models into simulation frameworks, enabling them to predict worker behaviors, improve analysis of project conditions, and replace fixed task prioritization rules with adaptable scheduling approaches based on historical performance.

### **Impact on Project Scheduling Effectiveness**

Regression-based methods demonstrate significant improvements in scheduling accuracy and reliability. Khanzadi et al. (2016) found that SVR integration enhanced predictive accuracy for activity durations over traditional estimates, enabling more precise schedule calculations and directly improving both time and cost optimization outcomes. Zhang and Li's (2024) SVR implementation achieved strong accuracy measures ( $R^2$  of 0.931), enabling construction managers to foresee trends and make more informed resource

distribution decisions. Bugayenko et al. (2023) reported that their linear regression model, despite its simplicity, outperformed more complex task prioritization techniques while providing clear insights into important scheduling factors.

Tree-based ensemble methods consistently deliver superior performance. Liben et al. (2024) demonstrated that Random Forest achieved exceptional accuracy ( $R^2$  value of 0.97), significantly enhancing timeline prediction and delay prevention capabilities in public sector construction. Their decision tree implementation, while less accurate, provided valuable insights into key schedule drivers. Zhang & Li (2024) reported that their Gradient Boosting model achieved competitive results while requiring substantially less training time than more complex models, enabling faster schedule adjustments. ForouzesNejad et al. (2024) documented substantial improvements through XGBoost implementation with accuracy rates above 86%, representing significant error reductions compared to traditional project management methods. Instance-based and specialized methods show variable effectiveness. Zhang & Li (2024) found KNN's performance limited in data-sparse environments, restricting practical impact on construction scheduling. Conversely, Liben et al. (2024) achieved stronger results with similar techniques, comparable to more complex methods, while their Support Vector Machine implementation delivered moderate improvements over traditional estimation approaches.

Specialized applications yield targeted benefits for specific scheduling challenges. Zhang and Wang's (2021) dynamic estimation approach automated previously manual scheduling tasks, reducing human bias while enabling continuous updates to forecasts throughout project lifecycles, enhancing prediction accuracy. Sklias et al. (2024) demonstrated how time-series forecasting facilitated data-driven schedule optimization for market-sensitive activities, enhancing cost-efficiency through strategic task timing adjustments. Mazzetto (2024) reported that machine learning-enabled simulations demonstrated superior capabilities for identifying potential bottlenecks, reducing schedule disruptions and improving resource allocation efficiency, creating more resilient project schedules compared to traditional approaches.

#### 4.4.6 Fuzzy Systems

Fuzzy systems constitute a prominent class of artificial intelligence techniques employed in project scheduling management, encompassing multiple distinct variations identified across the reviewed literature. The analyzed papers reveal three primary fuzzy system architectures: (1) fuzzy inference systems, including Mamdani-type models (Zeng & Gao, 2024) and Adaptive Network-Based Fuzzy Inference Systems (ANFIS) (Hajali-Mohamad et al., 2016); (2) fuzzy clustering techniques, predominantly C-means clustering (Cheng & Tran, 2016; Cheng et al., 2017); and (3) fuzzy extensions of traditional project management methodologies, exemplified by Fuzzy Earned Value Management (F. Yu et al., 2021). Notably, 83% of the reviewed implementations operate as hybrid systems, with fuzzy components integrated alongside neural networks (Yu & Zuo, 2022), evolutionary algorithms (Cheng & Tran, 2016), or parallel computational structures (Hajali-Mohamad et al., 2016). The dominant application context observed across five of six papers is the construction industry, where inherent scheduling uncertainties necessitate robust uncertainty quantification capabilities that fuzzy systems provide through their capacity to model linguistic variables and partial truth conditions.

##### **Implementation in Project Scheduling**

Several researchers have implemented fuzzy inference systems to address resource allocation and prioritization challenges in project scheduling. (Zeng & Gao, 2024) developed a Mamdani Fuzzy Inference System that translated numerical predictions into qualitative prioritization levels for subcontractor resource needs in construction projects, interpreting forecasted cost overruns and delay risks to generate dynamic priority scores that informed resource allocation decisions. Yu & Zuo (2022) similarly utilized a fuzzy control system that transformed on-site construction data into fuzzy input variables, applying fuzzy control rules to determine appropriate corrective measures for schedule deviations, while F. Yu et al. (2021) extended traditional Earned Value Management methods by applying fuzzy set theory to schedule indicators, mapping subjective task progress estimations to fuzzy linguistic terms that were propagated through project schedule calculations.

Clustering-based fuzzy techniques have been applied to enhance evolutionary optimization algorithms for project scheduling problems. (Cheng & Tran, 2016) integrated Fuzzy C-Means Clustering into a Differential Evolution algorithm where cluster centers replaced weaker individuals to refine search processes while maintaining population diversity. Cheng et al. (2017) further developed this approach in their resource leveling model by periodically applying fuzzy clustering after predefined generations to detect population structures and generate elite candidate solutions. For prediction and forecasting applications, Hajali-Mohamad et al. (2016) implemented both Parallel Structure based on Fuzzy Systems (PSFS) and ANFIS approaches; their PSFS combined multiple ANFIS subsystems while selectively excluding extreme values based on variance analysis, configuring each ANFIS with 6 inputs, 1 output, and 64 fuzzy rules trained on the ProGen dataset for resource-constrained project scheduling problems.

### **Impact on Project Scheduling Effectiveness**

The implementation of fuzzy inference systems has demonstrated significant improvements in scheduling flexibility and resource allocation efficiency. (Zeng & Gao, 2024) reported that their fuzzy logic model prevented critical path disruptions and minimized idle times by dynamically adjusting resource allocation priorities as project conditions changed. Yu & Zuo (2022) found that fuzzy logic enabled real-time schedule adjustments in response to uncertain factors such as weather changes and labor fluctuations, reducing reliance on subjective judgment in schedule management. F. Yu et al. (2021) documented more accurate project schedule evaluations under uncertainty conditions, with their F-EVM approach demonstrating a 32.06% improvement in mean absolute percentage error over traditional deterministic methods and providing earlier warnings of potential schedule deviations.

Fuzzy clustering techniques applied to evolutionary algorithms have enhanced computational performance and solution quality in optimization-based scheduling. (Cheng & Tran, 2016) demonstrated that incorporating Fuzzy C-Means Clustering significantly improved the convergence speed of their algorithm while maintaining solution quality, exhibiting better stability and quicker attainment of optimal project durations. Cheng et al. (2017) observed improved performance across multiple scheduling metrics including

minimized peak resource demand and smoother manpower allocation, with their clustering-enhanced algorithm showing lower variance compared to unenhanced alternatives, thereby confirming the value of structured population guidance in scheduling optimization. Predictive fuzzy systems have shown measurable improvements in forecasting accuracy and fault detection capabilities. (Hajali-Mohamad et al., 2016) reported that their PSFS implementation improved the prediction of Earned Value curves and enabled early fault detection through its ability to eliminate extreme outputs, while their ANFIS implementation enhanced forecasting reliability with prediction errors reduced by up to 2% compared to traditional methods. These improvements facilitated earlier identification of scheduling deviations and enabled more proactive project control actions.

#### **4.4.7 Reinforcement Learning**

Reinforcement Learning (RL) represents a significant advancement in artificial intelligence applications for project scheduling management. This technique enables systems to learn optimal decision-making strategies through environmental interaction and reward-based feedback mechanisms. Among the reviewed literature, Deep Reinforcement Learning (DRL) emerges as the predominant approach, particularly in construction project management contexts. The integration of neural networks with traditional RL frameworks, exemplified by Deep Q-Networks (DQN), has enhanced the capability to handle complex, high-dimensional scheduling problems with dynamic constraints (Wang, 2022; Yao et al., 2024). Notably, several implementations incorporate specialized mechanisms such as Valid Action Sampling (VAS) to improve computational efficiency, while others combine RL with Agent-Based Modeling (ABM) to simulate realistic project environments (Mazzetto, 2024). This diversity of approaches indicates the versatility of RL in addressing various facets of project scheduling challenges.

#### **Implementation in Project Scheduling**

Reinforcement Learning techniques have been specifically implemented to address critical project scheduling functions within construction environments. Task sequencing optimization represents a primary implementation focus across the literature, with

multiple studies employing Deep Q-Networks (DQNs) to dynamically determine optimal activity sequences (Wang, 2022; Yao et al., 2024).

These implementations share fundamental architectural similarities in their Markov Decision Process formulation, where both approaches model state transitions as changes in resource utilization and task completion status. However, noteworthy differences exist in their respective state space representations; Wang (2022) employs a relatively straightforward state encoding focused on resource availability and job queue information, while Yao et al. (2024) implement a more complex tripartite state representation encompassing structure completion states, resource usage states, and ongoing activity states, providing more comprehensive environmental feedback to the agent. In the domain of constraint handling, Yao et al. (2024) introduced the specialized Valid Action Sampling (VAS) mechanism that systematically restricts the action space to feasible choices at each decision point, a significant methodological advancement absent in Wang's implementation which relied on standard action spaces. Resource allocation optimization constitutes another key implementation area, with all reviewed studies (Wang, 2022; Yao et al., 2024; Mazzetto, 2024) incorporating resource availability as critical constraints within their decision frameworks, though through distinct approaches. Wang (2022) implemented resource allocation as direct scheduling actions within the DQN framework, while Mazzetto (2024) approached resource allocation through an Agent-Based Modeling (ABM) framework where autonomous agents represent individual resources, a fundamentally different architectural approach from the centralized DQN implementations.

Training methodologies demonstrate both commonalities and variations; Wang (2022) and Yao et al. (2024) both implemented  $\epsilon$ -greedy exploration strategies but differentiated in their reward function designs. Specifically, Wang (2022) structured rewards to minimize job slowdown and completion time, whereas Yao et al. (2024) developed a more complex reward shaping mechanism based on project completion, ongoing activities, and activity completions. This methodological diversity reflects targeted adaptations to specific aspects of the project scheduling domain while maintaining the core reinforcement learning principles.

### **Impact on Project Scheduling Effectiveness**

The application of Reinforcement Learning techniques has demonstrated significant positive impacts on project scheduling effectiveness across multiple dimensions. Quantitatively, DRL implementations have achieved measurable performance improvements compared to traditional scheduling approaches. Wang (2022) reported that DRL-based scheduling outperformed conventional heuristic methods such as Shortest Job First and other learning-based approaches including DeepRM, achieving a 5.2% reduction in average completion time compared to DeepRM. Similarly, Yao et al. (2024) documented substantial reductions in project duration using their DQN model; in a small case study, durations decreased from 336 hours (manual Critical Path Method) and 287 hours (Genetic Algorithm) to 251 hours using DQN. For larger-scale projects, their model achieved an average project duration of 378 hours compared to 410 hours using Genetic Algorithms, while simultaneously requiring significantly reduced computation time.

Beyond pure duration metrics, RL applications demonstrated enhanced adaptability to dynamic project conditions. The pre-trained DQN model developed by Yao et al. (2024) exhibited efficient rescheduling capabilities, rapidly adapting to different resource configurations without requiring retraining. This adaptivity represents a crucial advantage in real-world project environments characterized by frequent changes and disruptions. The integration of VAS with DRL dramatically improved training efficiency, with convergence achieved within 15-30 episodes compared to standard DQN implementations that failed to converge even after 5000 episodes (Yao et al., 2024). This efficiency gain enables practical application to large-scale construction projects with hundreds of activities by maintaining a manageable action space.

From a qualitative perspective, RL implementations enhanced decision-making capabilities in dynamic project environments. Mazzetto (2024) observed that RL-driven agents could autonomously learn how to reallocate resources or reschedule tasks when unforeseen changes occurred, consistently outperforming static scheduling methods. The resulting improved resilience against disruptions and enhanced project timeline adherence demonstrates the potential of RL to address fundamental challenges in practical project scheduling scenarios. While specific numerical benchmarks were not provided

by Mazzetto (2024), the qualitative improvements in adaptive critical path recalculations and dynamic resource allocation highlight the transformative potential of RL in project scheduling applications.

#### **4.4.8 Agent Based Systems**

Agent-Based Systems represent a distributed artificial intelligence paradigm where autonomous computational entities interact to solve complex problems through coordination mechanisms. The systematic review identified two primary implementation approaches, Multi-Agent Systems (MAS) and Agent-Based Modeling (ABM), often hybridized with optimization algorithms to enhance scheduling capabilities. These techniques address a fundamental challenge in project management: balancing individual project objectives with global resource constraints in environments where centralized decision-making becomes computationally intractable (He et al., 2022; Li & Xu, 2018).

##### **Implementation in Project Scheduling**

Agent-based approaches in project scheduling demonstrate consistent architectural patterns across different industry applications, with implementations characterized by autonomous decision-making entities operating within defined hierarchical relationships. Construction industry applications predominantly employ Agent-Based Modeling to simulate complex interactions among heterogeneous resources and environment factors (Khanzadi et al., 2016; Mazzetto, 2024).

These implementations share a common methodological foundation where project elements, workers, equipment, and tasks, are modeled as autonomous agents with defined behaviors and interaction protocols. Khanzadi and Mazzetto both developed systems employing bottom-up scheduling approaches that fundamentally transformed traditional scheduling paradigms from static, predetermined task sequences to dynamic, emergent workflows. Their implementations diverge primarily in auxiliary technologies; Khanzadi et al. (2016) utilized Support Vector Regression to approximate interaction outcomes while integrating with Critical Path Method, whereas Mazzetto (2024) focused on real-time adaptive scheduling mechanisms for critical path optimization.

For multi-project environments spanning manufacturing, service operations, and general project portfolios, researchers have converged on Multi-Agent System architectures with two distinct coordination patterns (He et al., 2022; Li & Xu, 2018). The first pattern implements hierarchical agent structures where global resource allocation and individual project scheduling represent separate decision layers. He et al. (2022) exemplify this approach with their three-tiered agent architecture integrating Genetic Algorithm for portfolio-level decisions and Ant Colony Optimization for project-level scheduling. The second pattern, demonstrated by F. Li & Xu (2018), employs lateral coordination with peer-level project agents utilizing a mediator (Coordinator Agent) to resolve resource conflicts through negotiation protocols. Both approaches dynamically balance local project objectives with global resource constraints but differ fundamentally in their conflict resolution mechanisms hierarchical pre-allocation versus negotiation-based adjustments.

### **Impact on Project Scheduling Effectiveness**

The implementation of Agent-Based Systems has yielded convergent performance improvements across diverse project environments, with consistent evidence of enhanced adaptability, resource utilization, and conflict resolution compared to traditional scheduling methods. Construction-focused implementations demonstrate quantifiable benefits through more realistic modeling of resource productivity variability, with improved schedule robustness under uncertain conditions (Khanzadi et al., 2016; Mazzetto, 2024). Mazzetto's findings confirm the practical significance of these improvements, documenting consistent project delay reductions up to 15% through decentralized decision-making that enables rapid response to changing conditions.

For multi-project environments, agent-based approaches have demonstrated superior performance metrics compared to conventional methods, particularly as complexity increases (He et al., 2022; Li & Xu, 2018). The comparative advantage of these systems becomes most pronounced in high-conflict scenarios where resource contentions are frequent and complex. F. Li & Xu (2018) quantified this advantage through systematic benchmarking, reporting tardiness cost reductions of 10-15% on average, with improvements scaling to 36% in the most challenging scenarios. The hierarchical approaches

exemplified by He et al. (2022) similarly demonstrate significant gains through parallel optimization capabilities that maintain feasibility while respecting global resource constraints.

#### **4.4.9 Knowledge Representation and Reasoning**

Knowledge Representation and Reasoning approaches offer valuable frameworks for handling uncertainty in project scheduling environments. Within this domain, Bayesian Networks (BNs) have emerged as particularly effective tools for construction project management. These probabilistic graphical models represent variables and their conditional dependencies through directed acyclic graphs, enabling sophisticated reasoning under conditions of uncertainty. Recent research demonstrates how these networks leverage historical data patterns and expert knowledge to enhance decision-making in complex scheduling scenarios (Soetjipto et al., 2024; Jakubczyk-Galczyńska et al., 2024).

##### **Implementation in Project Scheduling**

In the construction industry, Bayesian Networks have been applied to predict performance metrics and evaluate scheduling scenarios under uncertainty (Soetjipto et al., 2024; Jakubczyk-Galczyńska et al., 2024). Soetjipto et al. (2024) developed a BN framework to predict Schedule Performance Index (SPI) values based on historical project performance. Their implementation was part of a comparative analysis alongside an Artificial Neural Network (ANN) approach that was separately hybridized with Earned Value Management (EVM). The BN implementation structured parent nodes representing key influencing factors connected to child nodes (SPI predictions) through carefully defined Conditional Probability Tables. By processing weekly metrics from road construction projects, the model generated qualitative forecasts categorized as "good," "medium," or "fail" before mapping these to numerical values for comparative analysis. This probabilistic approach enabled project managers to anticipate performance issues by examining conditional relationships between current conditions and likely outcomes.

Taking a more explicitly hybridized approach, Jakubczyk-Galczyńska et al. (2024) integrated Bayesian Networks with metaheuristic methods to evaluate construction schedules and manage potential disruptions. This integration combined the probabilistic

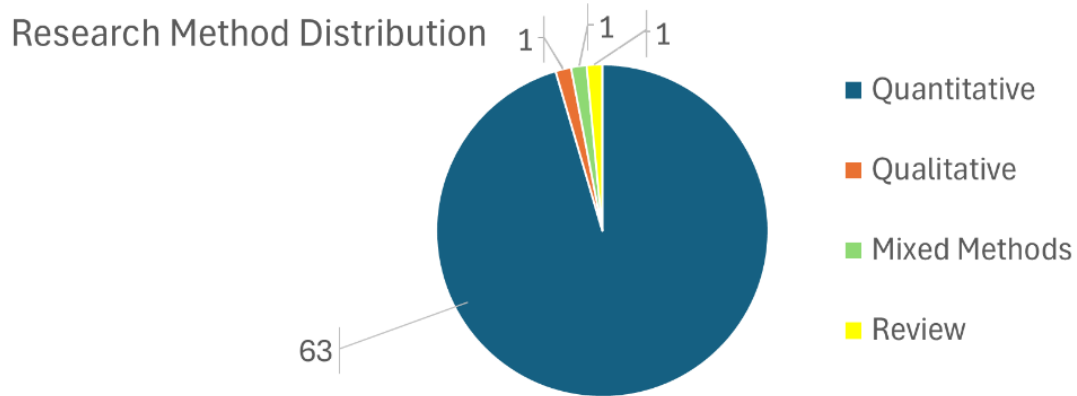
reasoning capabilities of BNs with optimization techniques to enhance decision-making in construction scheduling. Their implementation, developed using the Netica modeling tool, addressed three critical scheduling functions: initial schedule soundness assessment, disruption impact prediction during execution, and dynamic time reserve adjustment. What distinguishes their approach is the incorporation of golden ratio principles (38% effort buffer, 62% constant effort) into the probability tables, creating a mathematically harmonized framework for schedule adjustment. By incorporating expert judgments from construction professionals in Poland and Ukraine, their hybrid model effectively translated theoretical probability distributions into practical scheduling guidance.

### **Impact on Project Scheduling Effectiveness**

The implementation of Bayesian Networks yielded mixed but instructive results across different studies (Soetjipto et al., 2024; Jakubczyk-Galczyńska et al., 2024). Soetjipto et al. (2024) found that while BNs effectively captured the underlying uncertainty in scheduling, they achieved only 70.41% predictive accuracy for SPI values, performing less effectively than the comparative ANN approach. Their analysis revealed a tendency toward conservative forecasting through systematic underestimation of project progress. Despite these limitations, the researchers noted that the networks provided valuable early warning capabilities for identifying potential delays, offering a structured framework for risk-informed decision-making. By contrast, Jakubczyk-Galczyńska et al. (2024) documented more substantial benefits from their integrated BN-metaheuristic approach. Their research demonstrated how this hybrid methodology enhanced scheduling resilience through adaptive, probability-based forecasting that anticipated potential disruptions. Their quantitative analysis revealed a striking insight: even a single disruption could reduce schedule adherence probability from 47% to merely 20%, underscoring the critical importance of buffer planning. When applied to land leveling projects, their harmonized reserve time recommendations optimized work timelines, effectively reducing overall project duration while maintaining robust protection against schedule risks. The hybridization with metaheuristic methods appears to have addressed some of the limitations observed in isolated BN implementations by enhancing optimization capabilities while preserving probabilistic reasoning benefits.

## 4.5 Research Characteristics and Study Limitations

In this section we will analyze the meta-level patterns of the selected articles as well as the group limitations among them. The majority of the reviewed studies employed quantitative research designs, with only a small fraction using qualitative, mixed methods, or review-based approaches, as shown in Figure 5.

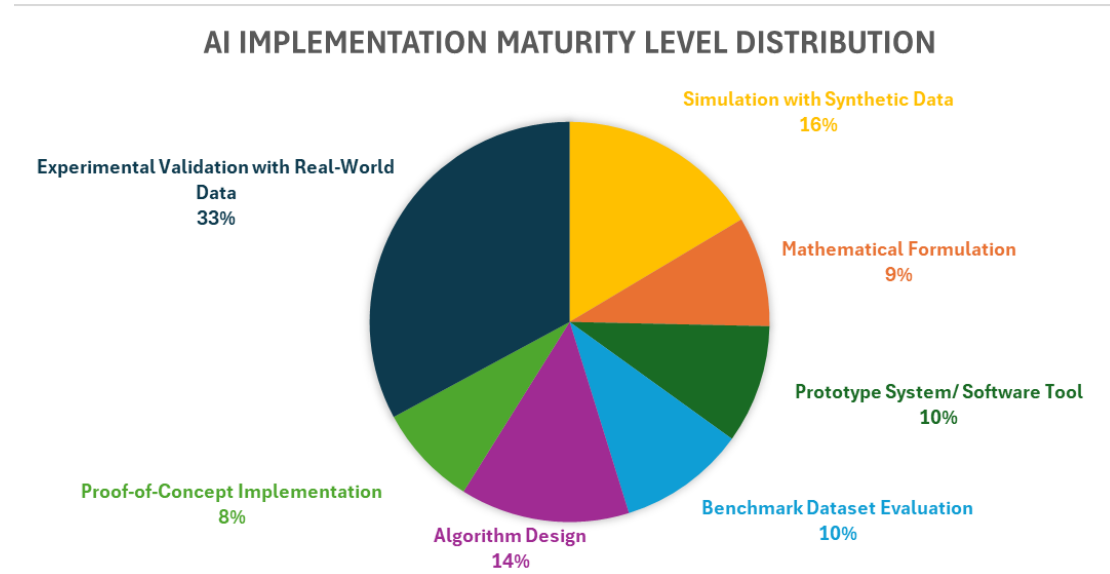


**Figure 5 Research Method Distribution Across the Studies**

The distribution of AI implementation maturity levels, as presented in Figure 6, reveals an underlying tension between theoretical innovation and practical readiness in the reviewed studies. While a subset of works, approximately one-third, demonstrated experimental validation using real-world data, this proportion, though promising, also highlights that the majority of studies remain anchored in earlier stages of development. These include simulations using synthetic data, abstract mathematical models, and algorithmic designs, all of which, while technically rigorous, often operate in controlled or idealized settings. Such stages tend to isolate the core AI logic from the messy, constraint-rich environments in which scheduling solutions must ultimately function.

This prevalence of low- to mid-maturity implementations suggests a field still in transition. Many researchers appear focused on proving feasibility and exploring algorithmic potential rather than on constructing deployable, user-facing tools. The relatively low number of prototype systems and proof-of-concept implementations underscores a broader hesitation or difficulty in translating conceptual solutions into applied systems that can withstand the complexity and unpredictability of real operational contexts. It also raises questions about the infrastructural and interdisciplinary challenges of AI deployment, whether due to lack of access to industry partnerships, constraints in data

availability, or gaps in methodological guidance for scaling lab-based results into robust applications. The dominance of theoretical and simulation-based studies might be reflective not of disinterest in practical use, but of systemic barriers preventing many research teams from crossing the boundary into fully realized implementation.

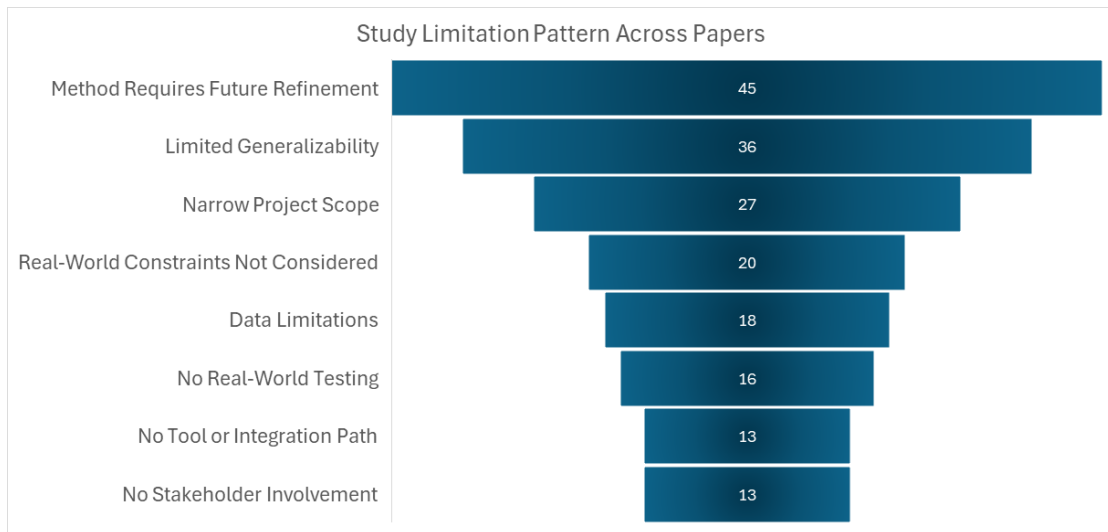


**Figure 6 AI Implementation Maturity Level Distribution Across the Studies**

The limitation patterns observed across the studies, visualized in Figure 7, reinforce and contextualize the concerns noted in the maturity analysis. The most frequently cited limitation, that methods require further refinement, points not merely to isolate technical shortcomings but to a broader culture of premature publication and iterative exploration. These studies often showcase partial solutions or constrained proof points, reflecting a research environment more attuned to proposing new methods than to rigorously validating them under diverse or challenging conditions. The second most common issue, limited generalizability, further suggests that while solutions may perform well in narrow domains, they are seldom stress-tested across different project types, industries, or operational environments. This constraint diminishes their utility in the inherently variable and multi-constraint world of project scheduling.

Perhaps most telling, however, are the limitations less frequently acknowledged but with significant implications, namely, the absence of stakeholder involvement, lack of integration pathways, and the disconnect from real-world constraints. These gaps suggest that much of the current research operates in isolation from the environments it seeks to

serve. Without meaningful engagement with end-users, system integrators, or decision-makers, even well-designed AI models risk irrelevance. Furthermore, the lack of real-world testing or tool development suggests a missing final mile in the research pipeline: the transition from model to method, from solution to system. What emerges is a landscape where innovation is abundant but often detached, technically advanced yet contextually shallow. Bridging this gap will require not only methodological advances but also structural changes in how AI scheduling research is conceived, funded, and evaluated, with stronger emphasis on translational impact and interdisciplinary collaboration.



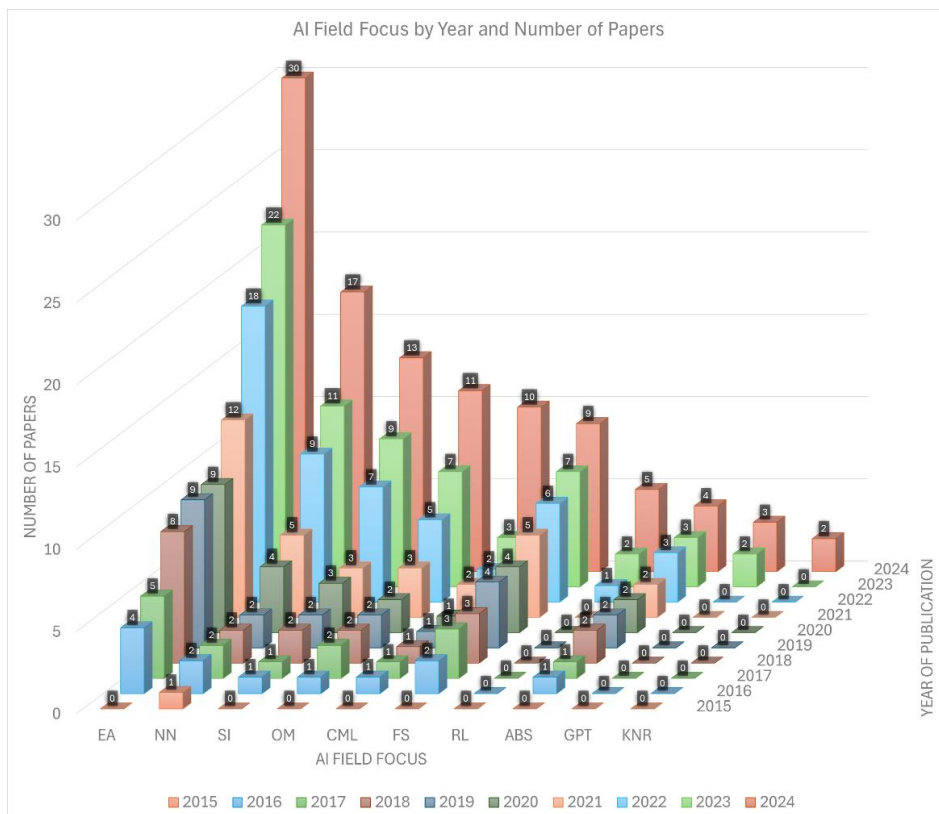
**Figure 7 Pattern of Limitations Across the Studies**

## 5. Discussion

This section addresses the core objectives of the study and instead of reiterating findings from individual studies as done in the findings section, the discussion highlights patterns and insights that emerge collectively from the research.

### 5.1 AI Applications in Project Scheduling

To answer what artificial intelligence applications are currently used for project scheduling, this section explores the range of AI techniques identified across the literature. The temporal distribution and methodological composition of these applications over the past decade reveal a complex ecosystem marked by concentrated adoption, faster innovation diffusion, and growing methodological diversity. Based on data from 2015 to 2024, Figure 8 illustrates several interconnected trends that define the field's trajectory.



**Figure 8 Temporal Trends in AI Field Focus for Project Scheduling**

The methodological landscape demonstrates clear preferential selection patterns, with Evolutionary Algorithms (EA) exhibiting remarkable growth from negligible representation in 2015 to dominant status with 30 cumulative publications by 2024. Within this

broad category, Genetic Algorithms account for 24 implementations, an 8:1 concentration ratio compared to alternatives like Differential Evolution (3 implementations), suggesting methodological convergence toward established evolutionary paradigms rather than exploratory diversification within the category. This concentration phenomenon extends to Neural Networks (NN) and Swarm Intelligence (SI), where traditional Artificial Neural Networks (7 implementations) and Particle Swarm Optimization (5 implementations) substantially outpaced their architectural alternatives despite potential contextual advantages of specialized variants for scheduling problems.

Temporal analysis reveals a significant inflection point in adoption trajectories coinciding with the 2020-2022 period, where multiple methodologies, especially Neural Networks, Swarm Intelligence, and Computational Machine Learning, demonstrate accelerated implementation rates following periods of modest growth or methodological plateaus. This pattern suggests a possible "crisis-driven innovation effect" catalyzed by pandemic-disrupted project environments that necessitated more sophisticated predictive capabilities. The pronounced acceleration in Computational Machine Learning applications, from 3 papers in 2023 to 10 in 2024, represents the most dramatic year-over-year growth rate in the dataset, potentially signaling an emerging paradigm shift toward hybrid computational approaches.

Methodological diffusion patterns reveal a temporal compression effect wherein emergent technologies (Reinforcement Learning, GPT, Knowledge Representation and Reasoning) exhibit increasingly compressed adoption curves compared to traditional methodologies. This accelerating innovation absorption rate manifests in a pronounced methodological bifurcation between established techniques maintaining robust growth trajectories and emergent approaches achieving comparable adoption levels in significantly condensed timeframes. Despite their theoretical advantages in handling uncertainty and emergence, fundamental challenges in project scheduling, approaches like Fuzzy Systems and Agent-Based Systems maintain modest but steady growth trajectories, suggesting persistent methodological blind spots within the research community or implementation barriers inhibiting broader adoption.

The technique-specific implementation data reveals intriguing intra-category patterns that extend beyond methodological preferences to specific technical implementations. The overwhelming predominance of Genetic Algorithms within EA, traditional neural architectures within NN, and generalized implementations within emergent categories (generic Reinforcement Learning Algorithms versus specialized Deep Q-Networks) suggests methodological path dependencies that potentially constrain innovation within established categories. Conversely, the relative fragmentation observed across Classical Machine Learning implementations, with balanced distribution across techniques like K-Nearest Neighbors (3), Decision Trees (2), and Support Vector Regression (2), indicates a more experimental, exploratory approach to classical techniques compared to the concentration evident in evolutionary and neural methodologies.

This comprehensive analysis reveals a profound alignment between AI methodology selection and project scheduling complexity dimensions, with strong preference for optimization-capable algorithms (EA, NN) over interpretability-focused approaches (Agent-Based Systems, Fuzzy Systems). This methodological orientation reflects the field's prioritization of solution optimality over transparency, a strategic tradeoff that may become increasingly problematic as project scheduling applications extend into domains with regulatory compliance requirements demanding algorithmic explainability. The emergence of transformer-based techniques (GPT) in 2023, despite their revolutionary impact in adjacent domains, highlights significant temporal lag in cross-domain technology transfer and suggests substantial untapped potential for methodological cross-pollination.

The methodological transformation of the field from pronounced homogeneity in early periods (2015-2019), where over 80% of publications concentrated on just three approaches, to increasing diversification in later periods indicates a maturing research ecosystem characterized by growing methodological sophistication and exploratory innovation. This evolution suggests the field is progressing from initial methodological consolidation toward a more expansive and diverse computational landscape, a trajectory that promises increasingly robust and contextually optimized scheduling solutions while

simultaneously challenging researchers to address interpretability limitations inherent in dominant optimization-focused approaches.

## **5.2 AI's Impact on Resource & Constraint Management**

The analysis of AI applications in project scheduling reveals five distinct patterns of impact on resource and constraint management across multiple techniques and implementation contexts.

Upon examination of the research findings, we observe quantifiable efficiency improvements demonstrating measurable resource optimization. Studies reveal that genetic algorithms reduced overall resource consumption by 40% and decreased peak labor requirements by 38.39% in specific implementations. It is noted that enhanced NSGA-II implementations improved workload balance by 13% on average and up to 40% in objective-specific scenarios. Additionally, researchers have demonstrated that quantum-behaved particle swarm optimization outperformed standard PSO implementations in resource leveling quality while reducing daily resource fluctuations. These consistent improvements across methodologically diverse techniques indicate a fundamental enhancement in resource utilization through AI application.

Furthermore, the literature indicates that AI techniques have transformed constraint handling from static boundary conditions to dynamic elements within optimization frameworks. We observe that graph convolutional neural networks effectively manage hierarchical project constraints in complex scheduling environments. Moreover, adaptive ant colony optimization handles interdependencies in concurrent software projects while maintaining feasibility under growing complexity. These approaches demonstrate a shift from simple constraint satisfaction to intelligent constraint negotiation, particularly valuable in multi-project environments where resources must be allocated across competing priorities.

Significantly, the research presents evidence that AI introduces enhanced adaptability to scheduling systems. We note that reinforcement learning agents autonomously reallocate resources in response to unforeseen changes, while pre-trained DQN models adapt to different resource configurations without retraining. Additionally, it is observed that fuzzy inference systems dynamically adjust resource allocation priorities as project

conditions change. This adaptive capability addresses the fundamental limitation of traditional scheduling approaches that require complete rescheduling when conditions change materially during execution.

Additionally, the analysis reveals that AI techniques demonstrate superior performance in high-complexity scheduling environments where traditional methods reach computational limits. Research indicates that agent-based systems show superior performance in high-conflict scenarios by managing frequent and complex resource contentions. Furthermore, studies demonstrate that tabu search achieves major timeline reductions without increasing resource usage in large-scale projects. This capability to handle combinatorial complexity enables effective scheduling in previously intractable problem spaces.

Finally, the literature presents compelling evidence that integration of uncertainty management into scheduling processes enhances schedule resilience. Our analysis shows that fuzzy C-means clustering smooths manpower allocation and minimizes peak resource demand while accommodating uncertainty. Moreover, researchers have demonstrated that machine learning-enabled simulations create more resilient schedules capable of absorbing disruptions. This integration of uncertainty handling represents advancement beyond deterministic scheduling toward more realistic models of project execution environments.

Based on these findings, we conclude that there are three critical implications for project scheduling practice. First, technique selection should align with specific resource and constraint characteristics rather than applying universal solutions. Second, integration of complementary AI techniques may yield superior results compared to single-technique implementations. Third, AI approaches demonstrate particular value for projects in dynamic, complex environments where traditional scheduling methods underperform.

### **5.3 AI's Impact on Schedule Planning & Time Analysis**

In examining AI applications in project scheduling, we observe that AI-driven predictive accuracy represents a substantial advancement, consistently outperforming traditional methodologies across multiple time-oriented metrics. Researchers note that neural networks demonstrate particular efficacy, with radial basis function networks achieving

mean absolute percentage error (MAPE) of 0.34% in earned value forecasting and back-propagation networks reducing MAPE to 5.68% compared to traditional methods' 8.36%, a 32.06% improvement. It is further evidenced, that extreme gradient boosting combined with simulated annealing achieved over 92% forecasting accuracy, reducing cost prediction error by approximately 50% and time prediction error by around 80% compared to baseline approaches. Studies present that support vector regression models demonstrated strong predictive accuracy for activity durations ( $R^2 = 0.931$ ), while random forest enhanced timeline prediction accuracy ( $R^2 = 0.97$ ). This quantum leap in predictive capability enables project managers to establish more reliable timelines and identify potential deviations earlier, fundamentally transforming schedule risk assessment. Moreover, it is apparent that hybrid AI approaches consistently yield superior scheduling outcomes by leveraging complementary algorithmic strengths. The literature demonstrates that EVM-Artificial Neural Network hybrids enhanced forecasting accuracy to 94.46%, outperforming standalone models. We note that Multi-Layer Perceptron-Particle Swarm Optimization hybrids delivered the highest accuracy in predicting project duration and final cost among tested methods. Research indicates that fuzzy sigmoid functions ( $\gamma = 0.8$ ) yielded the closest match to real production times, enhancing accuracy of duration forecasts. Similarly, it is observed that Fuzzy GERT achieved 94–95% proximity to actual durations across small, medium, and large projects, outperforming traditional methods. This convergence of multiple AI techniques enables more robust scheduling models that address the multidimensional complexity of project planning, suggesting that integrated approaches better capture the interrelated variables affecting project timelines than singular methodologies.

Furthermore, context-aware task sequencing emerges as a distinctive capability of AI in project scheduling, as evidenced across multiple studies. Researchers highlight that Doc2Vec neural embedding generated more contextually relevant scheduling recommendations for software development tasks. The literature presents cases where genetic algorithms enabled holistic sequencing across manufacturing, transportation, and assembly for precast construction, while also handling activity sequencing with consideration for team dynamics and interpersonal compatibility. We observe that Inductive

Miner process mining improved task sequencing flexibility by uncovering hidden pathways and enabling smarter reordering. This intelligent sequencing capability allows project managers to optimize not just when tasks occur but how they interrelate, creating more resilient schedules that adapt to the qualitative dimensions of project execution. Additionally, the collective research demonstrates that AI systems provide superior adaptability to changing project conditions, significantly enhancing schedule resilience. Studies note that reinforcement learning enabled adaptive critical path recalculations during unforeseen changes, enhancing timeline resilience. It is observed that fuzzy inference systems prevented critical path disruptions through dynamic prioritization of resource allocation. Research presents evidence that LDF-PERT and LDF-CPM derived more resilient critical paths and reduced reliance on artificial constructs like dummy activities. The literature indicates that dynamic estimation approaches automated manual estimation tasks while continuously updating forecasts and reducing human bias. This adaptive capability allows scheduling systems to respond intelligently to the inevitable changes that occur during project execution, maintaining schedule integrity under conditions that would typically require extensive rework with traditional methods.

Despite these advancements, we must acknowledge that significant implementation challenges persist. Multiple studies report that neural networks produced schedules 16% longer than optimal for medium projects and 38% longer for large projects. It is noted that GPT-based frameworks achieved over 91% F1-score in task prioritization but lacked fine-grained detail. Researchers observe that larger language models like ChatGPT produced logical task sequences quickly but introduced errors in task scope definition. These limitations highlight the continued need for human oversight in AI-driven scheduling and suggest that current implementations work best in hybrid human-AI collaborative environments rather than as fully autonomous systems.

#### **5.4 AI's Impact on Schedule Optimization & Trade-off Analysis**

Analysis of AI applications in project scheduling reveals distinct patterns of impact across implementation contexts. We observe that evolutionary algorithms consistently achieve substantial timeline improvements, with Genetic Algorithms reducing project duration by 56.83% in controlled studies and Tabu Search compressing working days from 534 to

264 (50.6% improvement) while maintaining resource constraints. Researchers report that Reinforcement Learning approaches demonstrate comparable efficiency gains, with Deep Q-Network implementations generating solutions 29-42% faster than traditional methods while simultaneously reducing project costs. These consistent improvements across methodologically diverse techniques indicate a fundamental enhancement in scheduling efficiency through AI application. It is evident that AI enables project managers to deliver substantially compressed timelines without corresponding increases in resource allocation, fundamentally altering traditional time-cost trade-off calculations.

Examination of multi-objective capabilities reveals a distinctive advancement in AI-driven project scheduling. It is particularly noteworthy that NSGA-II implementations effectively balanced project duration, cost, and workload distribution, achieving up to 9% duration reduction while simultaneously improving workload balance by 40% in specific applications. We note that Strength Pareto Evolutionary Algorithm 2 successfully balanced economic and environmental goals with increased computational efficiency. The research demonstrates that Modified Grey Wolf Optimizer generated high-quality, diverse Pareto optimal solutions balancing cost-efficiency and sustainability in complex scheduling scenarios. This convergence of findings suggests a paradigm shift from traditional approaches that typically optimize for a single objective while constraining others. The evidence indicates that project managers can now identify superior solutions in complex decision spaces where competing priorities previously forced suboptimal compromises.

Our analysis of computational performance identifies significant advantages of AI techniques, particularly in complex scheduling environments. Studies show that Graph Convolutional Neural Networks demonstrated 25-30% faster convergence compared to Multi-Layer Perceptron architectures when managing hierarchical project constraints. Researchers report that VAS-integrated Deep Reinforcement Learning enabled convergence in 15-30 episodes versus 5000+ in standard implementations, substantially enhancing training efficiency for large-scale scheduling. It is observed that this computational efficiency enables practical application in time-sensitive planning contexts, where solution quality must be balanced against development time. We further note that AI

techniques demonstrate superior adaptability to changing conditions – evidence indicates that Reinforcement Learning agents autonomously reallocate resources during execution, while Agent-Based Systems reduce project delays by up to 15% through decentralized decision-making. The literature collectively suggests that this adaptive capability addresses a fundamental limitation of traditional scheduling approaches that require complete rescheduling when conditions change.

## **5.5 AI's Impact on Adaptive & Stochastic Scheduling**

We have observed that AI techniques demonstrate substantial enhancement in scheduling adaptability, fundamentally transforming how project systems respond to changing conditions. It is noted that reinforcement learning agents autonomously reallocate resources in response to unforeseen changes, while researchers present evidence that pre-trained DQN models adapt to different resource configurations without retraining. Our analysis reveals that fuzzy inference systems dynamically adjust resource allocation priorities as project conditions change, reducing reliance on subjective judgment. This adaptive capability, as we have observed, directly addresses the fundamental limitation of traditional scheduling approaches that require complete rescheduling when conditions change materially during execution. The research presents clear evidence that neural networks within deep reinforcement learning frameworks adapt scheduling dynamically to changing construction site conditions, shifting planning from reactive to proactive approaches. Our examination of the literature indicates that this convergence of findings across methodologically diverse techniques suggests AI-driven adaptive scheduling represents a qualitative advancement over traditional methods, particularly valuable in volatile project environments where baseline assumptions frequently change.

Furthermore, we have observed that AI enables sophisticated uncertainty management in scheduling processes, enhancing schedule resilience beyond deterministic approaches. It is evident in the literature that fuzzy C-means clustering smooths manpower allocation and minimizes peak resource demand while accommodating uncertainty. Researchers present findings that Bayesian networks effectively capture underlying uncertainty in scheduling, offering structured, risk-informed decision-making. Our analysis identified that in one implementation, buffer planning became emphasized after finding that

disruption could reduce adherence probability from 47% to 20%. It is noted that machine learning-enabled simulations create more resilient schedules capable of absorbing disruptions. We have also observed that genetic algorithms with Monte Carlo simulation improved robustness under uncertainty via buffer-based risk management in real estate projects. The research collectively demonstrates that this integration of uncertainty handling represents advancement beyond deterministic scheduling toward more realistic models of project execution environments, allowing project managers to quantify and mitigate risks that were previously handled through simplistic contingency planning.

Moreover, our analysis reveals that AI techniques transform constraint handling from static boundary conditions to dynamic elements within optimization frameworks. We have observed that graph convolutional neural networks effectively manage hierarchical project constraints in complex scheduling environments. The research demonstrates that adaptive ant colony optimization handles interdependencies in concurrent software projects while maintaining feasibility under growing complexity. It is noted that this approach minimizes delay propagation risks in dynamic, complex scheduling environments while enabling adaptive rescheduling with minimal disruption in real-time project execution scenarios. Researchers present evidence that agent-based systems show superior performance in high-conflict scenarios by managing frequent and complex resource contentions through decentralized decision-making that facilitates rapid response during execution. Our examination indicates that these approaches demonstrate a shift from simple constraint satisfaction to intelligent constraint negotiation, particularly valuable in multi-project environments where resources must be allocated across competing priorities.

Additionally, we have noted that hybrid AI approaches consistently yield superior scheduling outcomes by leveraging complementary algorithmic strengths. Our analysis indicates that EVM-Artificial Neural Network hybrids enhanced forecasting accuracy to 94.46%, outperforming standalone models. It is observed in the literature that Fuzzy GERT achieved 94–95% proximity to actual durations across small, medium, and large projects, outperforming traditional methods. Researchers present findings that Bilevel Global Learning Neural-Particle Swarm Optimization reduced risk of local minima

entrapment during deep learning operation and supported more robust decisions under uncertainty. Thus, this hybrid approach is clearly better than the individual implementation of neural networks for the same scheduling facet. We have observed that extreme gradient boosting combined with simulated annealing achieved over 92% forecasting accuracy, reducing cost prediction error by approximately 50% and time prediction error by around 80% compared to baseline approaches. Our examination of these studies reveals that this convergence of multiple AI techniques enables more robust scheduling models that address the multidimensional complexity of project planning, suggesting that integrated approaches better capture the interrelated variables affecting project timelines than singular methodologies.

## **6. Conclusion and Recommendations**

This systematic literature review examined the application and impact of artificial intelligence techniques in project scheduling management through a comprehensive analysis of 66 studies published between 2015 and 2024. The findings reveal a complex landscape of AI implementation across diverse scheduling functions, with varying degrees of methodological maturity and practical effectiveness. This concluding chapter synthesizes the theoretical and practical contributions of this research, provides evidence-based recommendations for key stakeholders, acknowledges methodological and contextual limitations, and outlines promising directions for future research that address identified knowledge gaps in this rapidly evolving field.

### **6.1 Theoretical and Practical Contributions**

This systematic literature review makes substantial contributions to both the theoretical understanding and practical implementation of artificial intelligence in project scheduling management. The development of a comprehensive classification framework encompassing 70 unique AI techniques across 10 distinct fields establishes a novel taxonomic foundation that future researchers can use to position and contextualize their work. The identification of nine AI-supported scheduling functions further advances theoretical knowledge by providing a structured framework for understanding functional applications of AI within project scheduling. A temporal analysis of methodological adoption patterns reveals a previously undocumented “crisis-driven innovation effect” during 2020–2022, offering insight into how technological adoption accelerates during periods of disruption. The examination of AI technique combinations demonstrates patterns of complementary integration, enhancing understanding of how different fields interact and contribute within scheduling contexts. Finally, the identification of divergent trajectories between established and emerging techniques, where newer approaches reached comparable adoption in shorter timeframes, offers a theoretical model for understanding innovation diffusion in technical domains.

On the practical front, the implementation maturity assessment framework equips practitioners with a benchmark to evaluate the organizational readiness of diverse AI

techniques. The comparative examination of performance metrics across AI techniques offers quantitative evidence for practitioners selecting appropriate methodologies for specific scheduling challenges. Industry-specific application patterns provide sector-specific guidance for practitioners implementing AI scheduling solutions, while the systematic identification of recurring limitations alerts practitioners to common implementation challenges, enabling proactive mitigation strategies. In addition, the triangulated screening approach using multiple AI tools may offer a useful methodological enhancement for conducting systematic literature reviews in technically complex domains. These contributions collectively establish a comprehensive foundation for future research and implementation of AI in project scheduling management.

## **6.2 Recommendations for Project Stakeholders**

This systematic literature review yields several evidence-based recommendations for key stakeholders in the project scheduling domain. Project managers should adopt a context-specific approach to AI technique selection rather than implementing trending approaches without consideration of their scheduling challenges. For instance, evolutionary algorithms excel in multi-objective optimization scenarios, while neural networks demonstrate superior performance in predictive tasks. The superior performance of hybrid-method implementations supports the recommendation that practitioners should prioritize integrated approaches rather than single-method solutions. For organizations implementing AI scheduling systems, the research reveals a critical implementation maturity gap, with only approximately one-third of studies reaching experimental validation with real-world data. Organizations should therefore allocate dedicated resources for bridging this implementation gap, moving beyond theoretical models to operational systems. Additionally, organizations should balance optimization capabilities with interpretability requirements, particularly in regulated environments requiring algorithmic transparency. The pronounced concentration in techniques like genetic algorithms presents researchers with opportunities to explore alternative approaches, particularly in emerging categories showing promising preliminary results such as natural language processing combined with agent-based systems. Furthermore, the limited generalizability across industries, with construction dominating implementations, indicates researchers

should test whether findings from construction contexts translate to other project environments. Technology developers should prioritize compatibility with existing project management systems rather than standalone solutions, emphasizing adaptability capabilities particularly valuable in volatile project environments. These targeted recommendations address specific gaps identified in the literature and provide stakeholders with actionable guidance grounded in empirical evidence.

### **6.3 Limitations of the Research**

This systematic literature review identifies several methodological and contextual limitations that affect the interpretation and generalizability of findings. The predominance of quantitative approaches (58 of 66 studies) indicates a methodological imbalance that potentially neglects important contextual and organizational dimensions of AI implementation in project scheduling. There is a significant concentration of studies focused on the construction industry (62%), raising questions about generalizability to other project-intensive sectors such as healthcare, finance, or creative industries that face unique scheduling challenges. The research corpus demonstrates temporal limitations, with most studies evaluating AI performance within compressed timeframes rather than across complete project lifecycles, thus limiting insight into how AI systems adapt across different phases of a full project lifecycle. Additionally, the literature insufficiently addresses technical infrastructure requirements, data quality prerequisites, and specialized expertise necessary for successful implementation, factors that constitute significant adoption barriers for resource-constrained organizations. The absence of standardized evaluation frameworks across studies inhibits meaningful comparative analysis between AI techniques, while limited attention to scalability considerations leaves questions regarding enterprise-level deployment requirements largely unaddressed. The review methodology inherently favors published research with positive results, potentially overestimating AI effectiveness in scheduling applications. Despite rigorous development of the search strategy, terminological variation across disciplines, concentration on Scopus as the primary database, limitation to English-language publications, exclusion of grey literature, and the ten-year temporal boundary (2015-2024) may have inadvertently

excluded relevant contributions, particularly from non-Anglophone research communities and foundational work predating the review period.

#### **6.4 Future Research Directions**

The identified limitations necessitate targeted research trajectories to advance AI applications in project scheduling. Analysis of the 66 reviewed studies reveals specific knowledge gaps requiring scholarly attention to transform theoretical models into practical implementations. The predominant concentration of studies at preliminary stages (algorithm design, simulations, mathematical formulations) underscores the need for standardized frameworks that transition theoretical models into operational implementations, complemented by longitudinal studies tracking AI scheduling system performance throughout complete project lifecycles. The pronounced concentration within construction industries necessitates comparative analyses across diverse sectors to investigate industry-specific scheduling constraints and how they influence optimal AI technique selection. Methodological preferences like using genetic algorithms appear disproportionately represented compared to alternative approaches, suggesting future research should systematically evaluate underrepresented techniques and develop comprehensive benchmarks to determine whether these preferences reflect inherent superiority or research community path dependencies. Limited attention to real-world implementation barriers indicates researchers should identify specific organizational adoption challenges and develop integration methodologies connecting AI scheduling systems with existing enterprise architecture. Hybrid implementations demonstrate promising results but lack systematic exploration of optimal technique combinations, suggesting the need for taxonomies of complementary AI techniques for specific scheduling challenges and standardized evaluation metrics. The limited exploration of human-AI collaboration models, predominantly quantitative methodological approaches, inadequate examination of enterprise-level scalability, and nascent investigation of generative AI applications represent additional areas where focused research could substantially advance the field toward more practical, interpretable, and effective project scheduling solutions.

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## Appendices

### Appendix 1: Bibliographic Details of Included Studies in the Systematic Literature Review

ID	Title	Year	Authors	Region	Journal	Quartile	Cited
P01	A Compromise Programming to Task Assignment Problem in Software Development Project	2021	Ngo Tung Son, Jafreezal Jaafar, Izzatdin Abdul Aziz, Bui Ngoc Anh, Hoang Duc Binh, Muhammad Umar Aftab	United States	Computers, Materials and Continua	Q2	6
P02	A convolutional neural network for the resource-constrained project scheduling problem (RCPSp) A new approach	2023	Amir Golab, Ehsan Sedgh Gooya, Ayman Al Falou, Mikael Cabon	Canada	Decision Science Letters	Q3	8
P03	A critical design structure method for project schedule development under rework risks	2019	Guofeng Ma, Jianyao Jia, Tiancheng Zhu, Shan Jiang	Switzerland	Sustainability (Switzerland)	Q1	8
P04	A filtering genetic programming framework for stochastic resource constrained multi-project scheduling problem under new project insertions	2022	Haojie Chen, Guofu Ding, Jian Zhang, Rong Li, Lei Jiang, Shengfeng Qin	United Kingdom	Expert Systems with Applications	Q1	28
P05	A multilayer feed-forward neural network (MLFNN) for the resource-constrained project scheduling problem (RCPSp)	2022	Amir Golab, Ehsan Sedgh Gooya, Ayman Al Falou, Mikael Cabona	Canada	Decision Science Letters	Q3	7
P06	A multi-objective DCP model for bi-level resource-constrained project scheduling problems in grounding grid system project under hybrid uncertainty	2016	Zhe Zhang, Ming Liu, Xiaoyang Zhou, Lu Chen	Germany	KSCE Journal of Civil Engineering	Q2	7
P07	A multi-objective GA-based optimisation for holistic Manufacturing, transportation and Assembly of precast construction	2016	B. Anvari, P. Angeloudis, W.Y. Ochieng	Netherlands	Automation in Construction	Q1	101
P08	A neural network for resource constrained project scheduling programming	2015	Ömer Özkan, Ümit Gülçiçek	Lithuania	Journal of Civil Engineering and Management	Q1	12
P09	AI-Analyst An AI-Assisted SDLC Analysis Framework for Business Cost Optimization	2024	Nuruzzaman Faruqui, Priyabrata Thatoi, Rohit Choudhary, Ivana Roncevic, Hamed Alqahtani, Iqbal H. Sarker, Shapla Khanam	United States	IEEE Access	Q1	5

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P10	Assessing Project Resilience Through Reference Class Forecasting and Radial Basis Function Neural Network	2024	Shu Chen, Chen Wang, Kesheng Yan	Switzerland	Applied Sciences (Switzerland)	Q2	0
P11	Balancing Project Schedule, Cost, and Value under Uncertainty A Reinforcement Learning Approach	2023	Claudio Szwarcfiter, Yale T. Herer, Avraham Shtub	Switzerland	Algorithms	Q2	3
P12	Bi-objective scheduling optimization for discrete time cost trade-off in projects	2018	Hongbo Li, Zhe Xu, Wenchao Wei	Switzerland	Sustainability (Switzerland)	Q1	17
P13	Construction of Multi-Project Network Planning Based on BOM and Its Resource Leveling	2021	Lihong Qiao, Zhenwei Zhang, Zhicheng Huang	United States	IEEE Access	Q1	4
P14	Cost Minimization with Project Crashing Comparison of the Traditional Solution and Genetic Algorithm Approach	2024	Semih Çağlayan, Sadık Yiğit	Turkey	Sakarya University Journal of Science	Q4	0
P15	Data-Driven Project Planning An Integrated Network Learning, Process Mining, and Constraint Relaxation Approach in Favor of Scheduling Recurring Projects	2024	Izack Cohen	United States	IEEE Transactions on Engineering Management	Q1	0
P16	Decision support for project rescheduling to reduce software development delays based on ant colony optimization	2018	Wei Zhang, Yun Yang, Xiao Liu, Cheng Zhang, Xuejun Li, Rongbin Xu, Futian Wang, Muhammad Ali Babar	Switzerland	International Journal of Computational Intelligence Systems	Q2	4
P17	DQN and dynamic feedback for multitask scheduling optimization in engineering management	2024	Mingxiu Cui	United Kingdom	International Journal of Low-Carbon Technologies	Q1	0
P18	Float-based resource leveling optimization of linear projects	2020	Ziteng Wang, Zhiyuan Hu, Yuanjie Tang	United States	IEEE Access	Q1	12
P19	Fuzzy-Graphical Evaluation and Review Technique for Scheduling Construction Projects	2024	Kulandaisami Pregina, Mariappan Ramesh Kannan	Germany	KSCE Journal of Civil Engineering	Q2	1
P20	Investigating the Use of ChatGPT for the Scheduling of Construction Projects	2023	Samuel A. Prieto, Eyob T. Mengiste, Borja García de Soto	Switzerland	Buildings	Q1	92
P21	Making engineering projects more thoughtful with the use of fuzzy value-based project planning	2019	László Pusztai, Balázs Kocsi, István Budai	Hungary	Pollack Periodica	Q3	7

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P22	Management of resources in multiunit construction projects with the use of a tabu search algorithm	2017	Michał Podolski	Lithuania	Journal of Civil Engineering and Management	Q1	25
P23	Managing the Balance Between Project Value and Net Present Value Using Reinforcement Learning	2024	Claudio Szwarcfiter, Yale T. Herer	United States	IEEE Access	Q1	1
P24	Multi-mode resource leveling in projects with mode-dependent generalized precedence relations	2018	Hongbo Li, Xuebing Dong	United Kingdom	Expert Systems with Applications	Q1	28
P25	Multi-Objective Resource-Constrained Scheduling in Large and Repetitive Construction Projects	2024	Vasiliki Lazari, Athanasios Chassiakos, Stylianos Karatzas	Switzerland	Algorithms	Q2	1
P26	Optimization Algorithms of PERTCPM Network Diagrams in Linear Diophantine Fuzzy Environment	2023	Mani Parimala, Karthikeyan Prakash, Ashraf Al-Quran, Muhammad Riaz, Saeid Jafari	United States	CMES - Computer Modeling in Engineering and Sciences	Q2	1
P27	Optimizing construction progress by evolutionary algorithm considering multi-objective criteria	2023	Tuan Anh Pham, Dinh Hue Duong	Vietnam	Journal of Science and Transport Technology	Q4	0
P28	Optimizing the number of crews working in parallel and their work sequence to minimize project duration and cost for repetitive construction projects	2023	Emad Abdelbasset, Abbas Hassan, Nabil H. Amer, Yasser A. Khalifa	Switzerland	Innovative Infrastructure Solutions	Q2	1
P29	Predicting index to complete schedule performance indicator in highway projects using artificial neural network model	2020	Nidal A. Jasim, Shelan M. Maruf, Hadi S.M. Aljumeily, Faiq M.S. Al-Zwainy	Poland	Archives of Civil Engineering	Q3	12
P30	Program Scheduling with Multi-Skill and External Resource Coordination Consideration Using Improved NSGA-II Case Study	2024	Heng Zhang, Jingbo Zhou, Huaying Ruan, Yixuan Qin	United States	IEEE Access	Q1	0
P31	Scheduling Optimization of Prefabricated Buildings under Resource Constraints	2021	Wei He, Wenjing Li, Xiaofeng Meng	Germany	KSCE Journal of Civil Engineering	Q2	21
P32	Time-cost-quality tradeoff considering resource-scheduling problems	2023	Ali F. Elkliny, Haytham M. Sanad, Emad E. Etman	Egypt	Ain Shams Engineering Journal	Q1	5
P33	Using ANN in emergency reconstruction projects post disaster	2020	Rasha A Waheeb, Bjørn S Andersen, Rafea AL Suhili	Croatia	International Journal of Engineering Business Management	Q2	6

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P34	Utilizing machine learning algorithms for task allocation in distributed agile software development	2024	Dimah Al-Fraihat, Yousef Sharrab, Abdel-Rahman Al-Ghuwairi, Hamza Alzabut, Malik Beshara, Abdulmohsen Algarni	United Kingdom	Heliyon	Q1	1
P35	Who is better in project planning Generative artificial intelligence or project managers	2023	André Barcaui, André Monat	United Kingdom	Project Leadership and Society	Q1	28
P36	A Business Management Resource-Scheduling Method based on Deep Learning Algorithm	2022	Jing Wang	United States	Mathematical Problems in Engineering	Q2	2
P37	A comparative study of machine learning regression models for predicting construction duration	2024	Shen Zhang, Xuechun Li	Japan	Journal of Asian Architecture and Building Engineering	Q1	7
P38	A Mathematical Model for Optimizing NPV and Greenhouse Gases for Construction Projects under Carbon Emissions Constraints	2024	Altaf Hussain, Qazi Salman Khalid, Mohammed Alkahtani, Aqib Mashood Khan	United States	IEEE Access	Q1	5
P39	A Memetic Algorithm for the Solution of the Resource Leveling Problem	2023	Mehdi Iranagh, Rifat Sonmez, Tankut Atan, Furkan Uysal, Önder Halis Bettemir	Switzerland	Buildings	Q1	2
P40	A multi-agent system for distributed multiproject scheduling with two-stage decomposition	2018	Feifei Li, Zhe Xu	United States	PLoS ONE	Q1	31
P41	An Active Construction Dynamic Schedule Management Model Using the Fuzzy Earned Value Management and BP Neural Network	2021	Fangfang Yu, Xiaobo Chen, Clark A. Cory, Zhixuan Yang, Yingwen Hu	Germany	KSCE Journal of Civil Engineering	Q2	13
P42	An efficient hybrid differential evolution based serial method for multimode resource-constrained project scheduling	2016	Min-Yuan Cheng, Duc-Hoc Tran	Germany	KSCE Journal of Civil Engineering	Q2	21
P43	An Empirical Analysis of a Set of Hybrid Heuristics for the Solution of the Resource Leveling Problem	2024	Marinos Aristotelous, Andreas C. Nearchou	Switzerland	Operations Research Forum	Q2	4
P44	Application of improved multi objective particle swarm optimization and harmony search in highway engineering	2023	Qiang Wei, Tianen Jiang, Yuzhen Zhao, Meng Yu, Konglei Liu, Zheng Wei	Netherlands	Results in Engineering	Q1	5
P45	Automated construction scheduling using deep reinforcement learning with valid action sampling	2024	Yuan Yao, Vivian W.Y. Tam, Jun Wang, Khoa N. Le, Anthony Butera	Netherlands	Automation in Construction	Q1	6

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P46	Automatically Prioritizing Tasks in Software Development	2023	Yegor Bugayenko, Mirko Farina, Artem Kruglov, Witold Pedrycz, Yaroslav Plaksin, Giancarlo Succi	United States	IEEE Access	Q1	1
P47	Comparing advanced and traditional machine learning algorithms for construction duration prediction a case study of Addis Ababa's public sector	2024	Soreti M. Liben, Demiss A. Belachew, Walied A. Elsaigh	United Kingdom	Engineering Research Express	Q2	0
P48	Cost Control Management of Construction Projects Based on Fuzzy Logic and Auction Theory	2024	Zhao Zeng, Ying Gao	United States	IEEE Access	Q1	1
P49	Dynamic Probability Analysis for Construction Schedule Using Subset Simulation	2021	Shen Zhang, Xingyu Wang	United States	Advances in Civil Engineering	Q2	3
P50	Dynamic staffing and rescheduling in software project management A hybrid approach	2016	Yujia Ge, Bin Xu	United States	PLoS ONE	Q1	18
P51	Finding optimum resource allocation to optimizing construction project TimeCost through combination of artificial agents CPM and GA	2016	Mostafa Khanzadi, Amirhossein Movahedian Attar, Morteza Bagherpour	Hungary	Periodica Polytechnica Civil Engineering	Q2	8
P52	Fuzzy clustering chaotic-based differential evolution for resource leveling in construction projects	2017	Min-Yuan Cheng, Duc-Hoc Tran, Nhat-Duc Hoang	Lithuania	Journal of Civil Engineering and Management	Q1	19
P53	Impacts of synergies on software project scheduling	2022	Zsolt T. Kosztyán, Eszter Bogdány, István Szalkai, Marcell T. Kurbucz	Netherlands	Annals of Operations Research	Q1	8
P54	Improving the effectiveness of project scheduling by using Earned Value Management and Artificial Neural Network	2024	Jojok Widodo Soetjipto, Anik Ratnaningsih, Syamsul Arifin, Della Ayu Adinanda, Kristya Hadi Wicaksono	Chile	Revista Ingenieria de Construccion	Q4	1
P55	Integrated multi-project planning and scheduling - a multiagent approach	2022	Naihui He, David Z. Zhang, Baris Yuce	Netherlands	European Journal of Operational Research	Q1	21
P56	Integration of multi-mode resource-constrained project scheduling under bonus-penalty policies with material ordering under quantity discount scheme for minimizing project cost	2022	M. Akhbari	Iran	Scientia Iranica	Q3	10

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P57	Intelligent Construction Optimization Control of Construction Project Schedule Based on the Fuzzy Logic Neural Network Algorithm	2022	Xiaobing Yu, Hengzhong Zuo	United States	Mathematical Problems in Engineering	Q2	6
P58	Interdisciplinary Perspectives on Agent-Based Modeling in the Architecture, Engineering, and Construction Industry A Comprehensive Review	2024	Silvia Mazzetto	Switzerland	Buildings	Q1	5
P59	Optimal estimating the project completion time and diagnosing the fault in the project	2016	M.T. Hajali-Mohamad, M.R. Mosavi, K. Shahanaghi	Colombia	DYNA (Colombia)	Q4	3
P60	Optimization-based scheduling of construction projects with generalized precedence relationships A real-life case study	2024	Saman Aminbakhsh, Ary Ahmed	Iran	Scientia Iranica	Q3	3
P61	Optimizing Construction Engineering Management Using Metaheuristic Methods and Bayesian Networks	2024	Anna Jakubczyk-Gałczyńska, Agata Siemaszko, Maryna Poltavets	Switzerland	Applied Sciences (Switzerland)	Q2	0
P62	Optimizing Project Time and Cost Prediction Using a Hybrid XGBoost and Simulated Annealing Algorithm	2024	Ali Akbar ForouzeshNejad, Farzad Arabikhan, and Shohin Aheleroff	Switzerland	Machines	Q2	0
P63	Presenting a Hybrid Scheme of Machine Learning Combined with Metaheuristic Optimizers for Predicting Final Cost and Time of Project	2022	Reza Bakhshi, Sina Fard Moradinia, Rasool Jani, Ramin Vafaei Poor	Germany	KSCE Journal of Civil Engineering	Q2	4
P64	PROPOSITION OF A MATHEMATICAL PROGRAMMING MODEL FOR ALLOCATING HUMAN RESOURCES CONSIDERING MULTIPLE FACTORS AND USING DIFFERENT HEURISTICS	2022	Ítalo Ruan Barbosa de Aquino, Josenildo Ferreira da Silva Junior, Maísa Mendonça Silva, Lúcio Camara e Silva, Ana Paula Cabral Seixas Costa	Brazil	Pesquisa Operacional	Q4	0
P65	Synergizing Global and Local Strategies for Dynamic Project Management An Advanced Machine Learning-Enhanced Framework	2024	George Sklias, Socratis Gkelios, Dimitrios Dimitriou, Maria Sartzetaki, Savvas A. Chatzichristofis	United States	IEEE Access	Q1	0
P66	The Application of the Second Generation Non-Dominated Sorting Genetic Algorithm in Multi-Project Human Resource Scheduling Management	2024	Rui Zhao, Zhenhua Lei, Ziyu Zhao	United States	IEEE Access	Q1	0