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Thesis for the degree of Master of Science (M. A.)
in the field of Engineering management

"The Role of Data Analysis and Artificial Intelligence (AI) in Optimizing Systems Engineering Management Processes"

Supervisor:
Professor Taimur Narbaev
Co-Supervisor:
Flippo Maria Ottaviani

Author:
Atieh Tayarani Homayooni

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I would like to dedicate this work to my family, whose love, guidance, and endless support have shaped the person I am today. Their encouragement has always pushed me forward, even in the most challenging moments.

To my partner, for the constant support and encouragement throughout this journey.

ABSTRACT

The increasing complexity of modern engineering systems and the rapid growth of available data have created new challenges for Systems Engineering Management (SEM). Traditional management approaches are often insufficient for handling large volumes of operational data and complex decision-making processes. In this context, Artificial Intelligence (AI) and data analytics technologies provide significant opportunities for improving efficiency, optimizing system performance, and supporting data-driven decision making. This study investigates the role of Artificial Intelligence and data analytics in optimizing Systems Engineering Management processes.

To address this objective, a Systematic Literature Review (SLR) methodology was adopted to identify and analyze existing research in this field. Using a structured search process across major scientific databases, 73 peer-reviewed articles published between 2014 and 2025 were selected for analysis. The selected studies were examined using multiple analytical approaches, including descriptive analysis, statistical analysis, content analysis, trend analysis, and weighting analysis.

The results show that machine learning is the most frequently used Artificial Intelligence technique in engineering management applications. Operational data was identified as the most commonly used data type, reflecting the strong focus of existing studies on practical and operational improvements. The most prominent application domains include project management, supply chain management, construction engineering, and energy systems. Statistical analysis further revealed significant relationships between application domains, AI techniques, data types, and the outcomes achieved by these technologies.

Based on the findings, this research proposes the AI-SEM Maturity Matrix, a conceptual framework that maps Artificial Intelligence applications according to their technological sophistication and their scope within the Systems Engineering Management lifecycle. The framework highlights the current concentration of research in predictive analytics while identifying autonomous strategic decision-making systems as an important future research frontier.

Overall, the study demonstrates the growing importance of Artificial Intelligence in engineering management and provides a structured perspective on future research directions and practical implementation opportunities.

Keywords: Artificial Intelligence, Machine Learning, Systems Engineering Management, Data Analytics, Systematic Literature Review, Engineering Optimization.

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1. Chapter 1: Research Overview

1.1. Introduction

1.1.1. Systems Engineering in the Digital Era

Modern engineered systems are becoming larger, more interconnected, and more diverse than ever before. The integration of cyber-physical technologies, software-intensive architectures, digital infrastructures, and complex socio-technical interactions has significantly increased system complexity in sectors such as aerospace, energy, manufacturing, defense, and critical infrastructure. Because of this growing complexity, traditional reductionist engineering methods are often no longer sufficient to manage dynamic interactions, emergent behaviors, and uncertainties across the system lifecycle.

Systems Engineering (SE) provides an interdisciplinary approach to address these challenges. It supports the coordinated management of both technical and organizational aspects of complex systems. By focusing on stakeholder needs, structured requirements management, architectural integration, verification and validation, and lifecycle governance, SE helps ensure that systems are designed and managed in a consistent and systematic way. Its lifecycle perspective—spanning concept development, design, implementation, operation, maintenance, and retirement—ensures that system performance, reliability, and maintainability are addressed throughout the entire lifespan of the system.

However, the era of digital transformation has introduced new challenges. Large volumes of diverse data are now generated throughout the system lifecycle. Simulation outputs, testing reports, sensor data streams, operational logs, maintenance records, and stakeholder feedback all contribute to a complex ecosystem of information. As a result, organizations must learn how to effectively manage and leverage this data. The strategic use of lifecycle data has become essential for improving efficiency, reducing costs, enhancing quality, and maintaining competitiveness.

1.1.2. Challenges in Systems Engineering Management Processes (SEMP)

Systems Engineering Management Processes (SEMP) provide the governance framework that coordinates technical activities throughout the system lifecycle. These management processes include requirements definition, architecture development, system integration, verification and validation, configuration control, risk management, decision management, and project oversight. They are guided by internationally recognized standards such as **ISO/IEC/IEEE 15288** and the

INCOSE Systems Engineering Handbook. Together, these processes support the structured management of complex systems and ensure that technical implementation remains aligned with managerial decision-making. Because systems evolve over time, these processes are inherently iterative and interdependent.

Although these standards are well established, applying SEMP effectively in complex and data-intensive environments remains challenging. As systems grow in complexity, the interdependencies between components, subsystems, and stakeholders also increase. This makes it difficult to anticipate cascading failures or unintended consequences, particularly when systems exhibit emergent behavior and nonlinear interactions. Maintaining traceability across evolving requirements, design elements, and testing artifacts also becomes significantly more difficult.

Another major challenge is the propagation of uncertainty and risk throughout the system lifecycle. Issues such as schedule delays, budget overruns, design flaws, and integration problems often originate from early-stage information gaps that are not identified in time. Traditional risk management approaches typically rely on expert judgment and past experience rather than predictive mechanisms, which limits their ability to anticipate potential problems.

At the same time, the volume, velocity, and diversity of lifecycle data create significant data management challenges. Modern engineering environments generate large amounts of information from simulation outputs, issue tracking systems, configuration management tools, and operational monitoring platforms. These data sources are often fragmented and distributed across different systems, making it difficult to obtain a unified view. Without advanced analytical tools, extracting actionable insights from this heterogeneous data landscape can be both time-consuming and error-prone.

Finally, decision-making within SEMP is often reactive rather than predictive. Performance issues, quality problems, and resource inefficiencies are frequently identified only after their effects have already occurred. This reactive approach limits an organization’s ability to respond quickly and can lead to higher lifecycle costs. These operational and structural challenges highlight the need for more intelligent, data-driven mechanisms that can complement and enhance traditional Systems Engineering Management practices.

Artificial Intelligence as a Transformative Enabler of SEMP

Artificial Intelligence (AI) and advanced data analytics provide computational capabilities that can learn from historical data, detect complex patterns, generate forecasts, and support adaptive decision-making. Within the context of Systems Engineering Management Processes (SEMP), these capabilities enable a shift from traditional experience-based and reactive governance toward predictive, data-driven lifecycle management.

In SEMP, AI-enabled improvements can be conceptually grouped into three main areas. First, **predictive and risk-oriented intelligence** supports the proactive management of uncertainty. Machine learning models can analyze historical project performance, requirement volatility, defect records, and operational data to predict schedule deviations, cost overruns, and potential system failures. These predictive capabilities improve early risk identification and support more effective mitigation strategies.

Second, **optimization and resource intelligence** enhances the allocation of human, financial, and technical resources. AI-based optimization and prescriptive analytics can improve the accuracy of scheduling, workforce allocation, equipment utilization, and budget forecasting. As a result, these tools contribute to greater operational efficiency and reduced variability across the system lifecycle.

Third, **knowledge and process intelligence** strengthens key activities such as requirements engineering, traceability, quality assurance, and continuous process improvement. Techniques such as natural language processing, anomaly detection, and process mining enable organizations to extract actionable insights from both structured and unstructured lifecycle data. These approaches improve transparency and provide stronger decision support throughout the engineering process.

Taken together, these capabilities suggest that AI can significantly enhance traditional Systems Engineering Management models. However, although numerous studies have explored the application of AI in different areas of engineering, its integration into structured SEMP frameworks remains fragmented and uneven. Existing knowledge is still limited regarding which AI methods are applied to specific management processes, the maturity of these applications, and their overall impact on lifecycle governance. This gap highlights the need for systematic research and a structured overview of the current literature in this field.

1.2 Research Gap and Problem Statement

The growing body of research on the application of **Artificial Intelligence (AI)** in engineering and management highlights its strong potential to improve efficiency, quality, and decision-making. Many studies report successful uses of machine learning for risk prediction, natural language processing for requirements analysis, anomaly detection for fault diagnosis, and optimization algorithms for resource allocation. Together, these contributions illustrate the transformative role that AI can play across different phases of the lifecycle of complex systems.

Despite the increasing number of publications in this area, the existing literature still presents several important limitations. First, research remains highly fragmented across domains such as construction management, manufacturing systems, supply chain optimization, software engineering, energy systems, and IT operations. Although these studies demonstrate successful applications in specific contexts, they rarely place AI implementations within the broader framework of the **Systems Engineering Management Process (SEMP)** lifecycle. As a result, the relationship between specific AI techniques and particular management processes often remains unclear when viewed through established standards such as **ISO/IEC/IEEE 15288** and the guidelines provided by the **INCOSE Systems Engineering Handbook**.

Second, much of the current research focuses on isolated technical implementations rather than lifecycle-level integration. Many studies aim to improve a single task—such as predicting project delays, detecting defects, or forecasting maintenance needs—without examining how these solutions interact with broader governance structures, traceability mechanisms, or cross-process coordination within SEMP.

Third, the maturity and depth of AI adoption in Systems Engineering contexts have not been systematically evaluated. The literature lacks a unified framework for determining whether AI applications operate at descriptive, predictive, prescriptive, or autonomous levels. In addition, existing research rarely classifies AI applications according to their scope of influence, such as operational, process, design, or strategic management levels.

Fourth, a comprehensive mapping of AI techniques, data types, and application domains to Systems Engineering Management Processes has not yet been developed through a systematic synthesis of the literature. While individual case studies and review papers exist, the absence of a consistent analytical framework makes it difficult to identify research trends, methodological patterns, and emerging gaps in the field.

These limitations highlight the need for a systematic literature review that synthesizes and organizes existing knowledge on AI applications in the context of SEMP. Such an analysis can help identify key thematic and methodological trends, evaluate the maturity of current implementations, and reveal underexplored areas that require further investigation.

In response to these gaps, this thesis conducts a systematic literature review of AI applications relevant to Systems Engineering Management. Building on this analysis, the study proposes an analytical maturity framework—the **AI-SEM Maturity Matrix**—designed to evaluate both the extent of AI integration and the technological depth of AI implementations within lifecycle management processes.

1.3 Research Objectives

1.3.1. Main Objective

The main objective of this research is to explore and evaluate the application of Artificial Intelligence (AI) and data analytics methods within Systems Engineering Management Processes (SEMP), and to develop a structured analytical framework for assessing the extent and depth of AI integration throughout the system lifecycle.

1.3.2. Sub-Objectives

1. To conduct a systematic review of peer-reviewed literature addressing the application of AI in Systems Engineering Management.
2. To classify AI techniques, data types, and application domains within SEMP using a structured coding and classification approach.
3. To analyze the relationships between AI methods, application areas, data sources, and reported outcomes through descriptive and inferential analytical techniques.
4. To identify research trends, thematic focal points, and underexplored areas at the intersection of AI and Systems Engineering Management.
5. To develop an **AI–SEM Maturity Matrix** that evaluates both the scope of AI application across lifecycle domains and the level of technological sophistication, including the degree of automation involved in AI integration.
6. To provide structured recommendations for future research directions and for the strategic adoption of AI in Systems Engineering Management.

1.4 Research Questions

1.4.1 Main Research Question

What is the current level and extent of integration of Artificial Intelligence (AI) and data analytics methods within Systems Engineering Management Processes (SEMP)?

1.4.2 Sub-Research Questions

1. Which Systems Engineering Management Processes are most frequently addressed in research on AI applications?
2. Which AI and data analytics methods are applied across different areas of SEMP?
3. What types of data and analytical approaches are most commonly used in AI-based SEMP applications?
4. What thematic patterns, research trends, and methodological concentrations can be identified in the existing literature?
5. What research gaps and underexplored areas exist at the intersection of AI and Systems Engineering Management?
6. How can the maturity of AI integration in SEMP be conceptually assessed through a structured analytical framework?

1.5 Research Contributions

This thesis contributes to the emerging intersection of Artificial Intelligence and Systems Engineering Management in several ways.

1. Systematic consolidation of AI applications in SEMP This study provides a structured and reproducible systematic literature review of peer-reviewed research addressing the use of Artificial Intelligence and data analytics techniques within Systems Engineering Management Processes. By synthesizing studies scattered across multiple engineering domains, the thesis offers a consolidated overview of current research developments.

2. Thematic and process-oriented classification framework AI applications are systematically categorized according to their corresponding SEMP domains, lifecycle stages, data types, and analytical techniques. This structured classification enables comparative analysis and helps identify dominant application areas as well as underexplored domains.

3. Analytical evaluation of methodological and technological trends Through descriptive and inferential analysis, the thesis examines relationships between AI techniques, application domains, and data sources. This analysis provides insights into methodological concentrations, emerging research trends, and patterns of technological adoption within the literature.

4. Identification of research gaps and underdeveloped areas By mapping the existing research landscape, the study highlights thematic imbalances, gaps in lifecycle coverage, and areas where AI integration remains limited or underdeveloped. These findings support evidence-based recommendations for future research.

5. Development of the AI–SEM Maturity Matrix The thesis proposes a structured maturity framework that evaluates AI integration in Systems Engineering Management across two dimensions: lifecycle scope and technological depth. The AI–SEM Maturity Matrix serves as a conceptual tool for assessing the progression of AI adoption from descriptive analytics toward predictive, prescriptive, and autonomous capabilities.

6. Strategic guidance for future AI-enabled Systems Engineering Based on the systematic findings and maturity assessment, the study provides structured recommendations for advancing AI integration in both research and practical applications of Systems Engineering Management.

1.6 Scope and Delimitations

This research focuses on the systematic investigation of Artificial Intelligence (AI) and data analytics applications relevant to Systems Engineering Management Processes (SEMP). The scope of the study is limited to peer-reviewed academic publications that address AI techniques within engineering management and system lifecycle contexts.

The research is bounded by the following delimitations:

1. Literature-based analysis The study employs a systematic literature review methodology and does not include empirical experimentation, field implementation, surveys, or the development of primary case studies.

2. Process-oriented focus The analysis concentrates specifically on Systems Engineering Management Processes as defined by established standards such as ISO/IEC/IEEE 15288 and the guidelines provided by INCOSE. AI applications that are not directly related to lifecycle governance or engineering management processes are excluded from the analysis.

3. Technological scope The study examines AI and data analytics techniques including machine learning, deep learning, natural language processing, optimization algorithms, and process mining. Broader digital transformation technologies that do not involve analytical or intelligent mechanisms fall outside the scope of this research.

4. Language and publication criteria Only accessible, peer-reviewed academic sources published in English and Persian were considered within the defined selection criteria.

5. Conceptual maturity assessment The proposed **AI–SEM Maturity Matrix** is developed as a conceptual analytical framework derived from the synthesis of the reviewed literature. Its validation through empirical industrial implementation is outside the scope of this thesis.

These delimitations ensure methodological clarity and define the boundaries within which the study's conclusions and recommendations are formulated.

1.7 Thesis Structure

This thesis is organized into seven chapters.

- **Chapter 1** introduces the research context, defines the problem statement, outlines the research objectives and questions, and presents the contributions, scope, and structure of the study.
- **Chapter 2** reviews the relevant literature on Systems Engineering Management and Artificial Intelligence applications, establishing the theoretical and conceptual foundation for the research.
- **Chapter 3** describes the research methodology, including the systematic literature review protocol, search strategy, inclusion and exclusion criteria, and analytical procedures.

- **Chapter 4** presents the results of the literature analysis, including thematic classification, statistical evaluation, and the identification of research trends.
- **Chapter 5** discusses the findings in relation to Systems Engineering Management practices and emerging technological developments.
- **Chapter 6** introduces the **AI–SEM Maturity Matrix** and synthesizes the identified research gaps and strategic implications.
- **Chapter 7** concludes the thesis by summarizing the main contributions, outlining the study's limitations, and proposing directions for future research.

2. Chapter 2 : Theoretical Foundation and Literature Review

2.1 Introduction

This chapter provides the theoretical and conceptual foundation for the present study. Since this research examines the role of Artificial Intelligence and data analytics in Systems Engineering Management, it is necessary to first clarify the main concepts related to systems engineering, lifecycle thinking, engineering management processes, and the use of intelligent technologies in complex operational environments.

The chapter is structured in two main parts. The first part reviews the theoretical foundations of systems engineering and systems engineering management, including lifecycle models, engineering methodologies, and process optimization. The second part examines the research background related to Artificial Intelligence and data analytics, with particular attention to their practical applications in engineering and management contexts.

By combining theoretical discussion with a review of previous studies, this chapter establishes the academic basis for the systematic literature review presented in Chapter 3 and supports the interpretation of the findings developed in the subsequent chapters.

2.2 Theoretical Foundation

2.2.1 Systems Engineering (SE)

2.2.1.1 Definition, Principles, and Importance of Systems Engineering in Developing Complex Systems

Systems Engineering (SE) is widely recognized as an interdisciplinary and collaborative approach to the design, development, implementation, and management of complex systems. Its primary objective is to ensure that a system fulfils stakeholder needs while maintaining consistency across technical, operational, and managerial dimensions. Rather than focusing only on individual components, Systems Engineering adopts a holistic perspective that emphasizes the interactions and dependencies among system elements [20].

A defining characteristic of Systems Engineering is its interdisciplinary nature. The development of complex systems usually requires the integration of multiple fields such as mechanical engineering, electronics, software engineering, and management. For this reason, effective collaboration among specialists from different disciplines is essential. In addition, Systems Engineering places strong emphasis on continuous communication with stakeholders, including customers, end-users, managers, and other affected parties, in order to identify and refine requirements throughout the system lifecycle [20].

Another core principle of Systems Engineering is its focus on the system as a whole. This holistic perspective helps engineers understand how different components interact and how changes in one part of the system may affect overall performance. Such an approach is particularly important in complex systems, where local decisions can have broader consequences at the system level. Ultimately, the goal of Systems Engineering is to ensure that the final system satisfies both functional and non-functional requirements, including performance, reliability, safety, and maintainability [21].

The principles of Systems Engineering provide a structured basis for managing system development effectively. These principles include clear requirements definition, complexity management, lifecycle-oriented design, iterative development, risk analysis, verification and validation, and interoperability [22]. Requirements definition is especially critical because a clear understanding of stakeholder expectations forms the foundation for successful system development. Likewise, verification and validation ensure that the system is built correctly and that it fulfils its intended purpose in practice.

The importance of Systems Engineering becomes more evident as systems increase in scale and complexity. Complex systems are typically characterized by a large number of interconnected components, non-linear interactions, unpredictable behaviour, and operation in dynamic environments [23]. These characteristics make system development more difficult and increase the likelihood of integration problems, delays, and unexpected failures if a structured engineering approach is not applied.

Without Systems Engineering, the development of complex systems may face significant challenges, including cost overruns, schedule delays, reduced quality, and failure to meet stakeholder requirements [20]. Systems Engineering addresses these risks by providing a systematic framework that connects requirements analysis, system design, implementation, verification and validation, deployment, and maintenance activities [24]. Because the process is iterative, feedback from later stages can be used to improve earlier decisions and enhance overall system performance.

For these reasons, Systems Engineering is considered essential for the successful development of complex systems. By applying its principles and methods, organizations can better manage complexity, reduce technical and operational risks, improve system quality, and increase the likelihood that the final system will satisfy stakeholder needs.

2.2.1.2 System Lifecycle (SLC) and Its Various Stages

The System Lifecycle (SLC) refers to the sequence of stages that a system passes through from its initial conception to its eventual retirement. It provides a structured framework for managing the complexity of system development and ensuring that system-oriented projects are executed effectively. Selecting an appropriate lifecycle model depends on several factors, including the nature of the system, the level of project risk, and stakeholder requirements [25].

Several lifecycle models have been proposed in systems engineering literature, such as the **Waterfall model, Spiral model, Agile model, and the V-Model**. Each model offers a different approach to organizing development activities and managing project uncertainty. Among these approaches, the **V-Model** is widely recognized for its strong emphasis on verification and validation throughout the development processThe structure of the V-Model and the relationship between development and testing phases are illustrated in **Figure 1**.

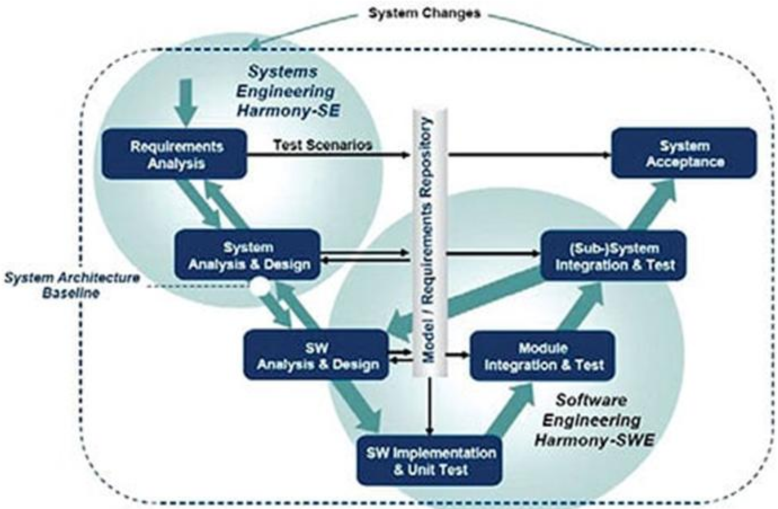

Figure 2.1 Model illustrating the relationship between system development phases and corresponding verification and validation activities

The **V-Model**, also referred to as the **Verification and Validation (V&V) model**, establishes a clear relationship between development activities and their corresponding testing procedures [26]. The model is typically represented in the form of the letter “V”, where the left side illustrates the development phases and the right side represents the associated testing phases. This structure ensures that each stage of development is accompanied by a corresponding validation activity.

The V-Model is particularly suitable for systems that require **high reliability and strict quality assurance**, such as systems in **medical, aerospace, and military domains** [27].

Development Stages (Left Side of the V)

The left branch of the V-Model represents the system development phases, where requirements are gradually refined into detailed design specifications.

Business Requirements Definition : This initial stage focuses on identifying the overall objectives of the system and understanding stakeholder expectations. At this level, high-level requirements are documented and the general project scope is defined. The primary output of this stage is the **Business Requirements Document (BRD)**.

System Requirements Definition : During this stage, the previously identified business requirements are translated into detailed and measurable system requirements. These requirements include both **functional requirements** and **non-functional requirements**, such as reliability, security, performance, and efficiency. The result of this stage is the **System Requirements Specification (SRS)**.

System Architectural Design : At this stage, the overall architecture of the system is designed. This includes defining the major components, interfaces, and interactions between system modules. The system architecture must ensure that all specified requirements can be fulfilled. The outcome of this stage is typically documented in the **System Architectural Design Document (SADD)**.

Detailed Design : The detailed design phase focuses on specifying the internal structure and functionality of each system component. This may include database structures, algorithms, user interface specifications, and other technical implementation details. The main output of this phase is the **Detailed Design Document (DDD)** [28].

Testing Stages (Right Side of the V)

The right branch of the V-Model represents the **testing and validation phases**, which correspond directly to the development stages on the opposite side of the model. This structured alignment ensures that every design activity is verified through an appropriate testing procedure.

Unit Testing : Unit testing focuses on evaluating individual components of the system independently. The objective is to verify that each component functions correctly according to the specifications defined during the detailed design stage.

Integration Testing : Integration testing examines how different components interact with each other when combined into subsystems. This stage ensures that the interfaces between system modules operate correctly and that integrated components perform as expected.

System Testing : System testing evaluates the entire system as a complete and integrated unit. The purpose of this stage is to verify that the system fulfils all defined system requirements specified in the **System Requirements Specification (SRS)**.

Acceptance Testing : Acceptance testing represents the final stage of the validation process and is typically performed by end users or stakeholders. The goal is to confirm that the system satisfies the original business requirements defined in the **Business Requirements Document (BRD)** and meets stakeholder expectations [29].

Advantages and Limitations of the V-Model

The V-Model provides several advantages for system development, particularly in projects that require strong quality assurance and structured validation procedures [29].

Emphasis on Verification and Validation : One of the main strengths of the V-Model is its strong focus on verification and validation throughout the development lifecycle. Each development phase is directly linked to a corresponding testing phase, which helps ensure that the final system satisfies stakeholder requirements.

Early Detection of Errors : Because testing activities are planned alongside development phases, potential errors and inconsistencies can often be identified at earlier stages of the project. Early detection of issues reduces the cost and effort required for corrections during later stages.

Clarity and Structured Development : The V-Model follows a well-defined and structured process, which makes it relatively easy to understand and implement. This clarity helps project teams maintain consistency and transparency throughout the development process.

Despite these strengths, the V-Model also presents several limitations that should be considered when selecting an appropriate development methodology [29].

Inflexibility: The V-Model follows a rigid and sequential structure. As a result, modifications made in the early phases can lead to significant changes in later stages, potentially increasing both development time and project costs.

Limited Suitability for Dynamic Projects : Projects characterized by rapidly changing requirements or high levels of uncertainty may not be well suited to the V-Model. Its linear structure makes it difficult to adapt quickly to evolving project conditions.

Delayed User Feedback : In many cases, feedback from end-users or customers is obtained only during the later testing stages. This delay may result in the identification of major issues relatively late in the development process, making them more difficult and costly to resolve.

Extensive Documentation Requirements: The model requires comprehensive documentation at each stage of development. While documentation can improve traceability and accountability, excessive documentation may also increase administrative workload.

Limited Suitability for Small Projects: For small or low-complexity projects, the structured nature of the V-Model may introduce unnecessary overhead and increase project duration.

High Expertise Requirements: Designing appropriate tests that correspond to each development phase requires substantial technical knowledge and experience, particularly in system validation and software testing.

Weak Risk Management Mechanisms: The V-Model does not inherently include a strong mechanism for continuous risk management throughout the lifecycle. As a result, some risks may only become apparent during later stages of development.

While traditional systems engineering methodologies such as the V-Model provide structured approaches for system development, modern engineering environments increasingly require more intelligent and adaptive solutions. In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools for improving decision-making, optimization, and automation within systems engineering processes.

2.2.1.3 SE Methodologies: V-Model, Spiral Model, and Agile SE

Several development methodologies have been proposed within systems engineering and software engineering to support the design and implementation of complex systems. Among the most widely discussed approaches are the **V-Model, Spiral Model, and Agile Software Engineering (Agile SE)**. Each methodology follows a different development philosophy and offers specific advantages depending on project requirements, risk levels, and system complexity. The following sections provide a brief overview and comparison of these approaches.

1. V-Model

The **V-Model** is a linear and sequential development methodology in which each development phase is directly associated with a corresponding testing phase. In this model, design and implementation activities are closely linked to validation activities, ensuring that every stage of development is verified through appropriate testing procedures. The V-Model therefore places strong emphasis on **verification and validation (V&V)** throughout the system lifecycle.

The main stages of the V-Model include the following [30]:

- **Requirements Analysis:** Identification and documentation of user and system requirements.
- **High-Level Design:** Definition of the overall system architecture and major system components.
- **Low-Level Design:** Detailed specification of individual modules and system components.
- **Implementation:** Coding and construction of the system according to the design specifications.
- **Unit Testing:** Verification of individual modules to ensure correct functionality.
- **Integration Testing:** Evaluation of interactions between integrated modules.
- **System Testing:** Testing the entire system as a unified entity.

- **Acceptance Testing:** Final validation performed by the end-user to confirm that the system meets specified requirements.

The main advantages of the V-Model include the following:

- **Clear and Structured Development Process:** The sequential structure provides a well-defined development path.
- **Strong Emphasis on Testing:** Continuous verification improves system reliability and reduces the likelihood of defects.
- **Suitability for Stable Projects:** The model is particularly appropriate when system requirements are clearly defined and unlikely to change.

However, the V-Model also presents several limitations:

1. **Limited Flexibility:** Changes introduced in later stages can be costly and difficult to implement.
2. **Delayed User Feedback:** End-user involvement typically occurs only during later testing stages.
3. **Extensive Documentation Requirements:** Each phase requires detailed documentation.

2. Spiral Model

The **Spiral Model** is an iterative development methodology that emphasizes **risk management** throughout the project lifecycle. The model combines elements of both iterative development and systematic risk assessment, making it particularly suitable for large and complex projects.

Each iteration of the spiral consists of four major phases [31]:

- **Objective Definition:** Identification of goals, constraints, and alternative solutions for the current iteration.
- **Risk Assessment:** Analysis and evaluation of potential risks associated with the proposed solutions.
- **Development and Testing:** Implementation and validation of system components based on the identified objectives.

- **Planning the Next Iteration:** Preparation for the subsequent development cycle.

The advantages of the Spiral Model include [31]:

- **Strong Risk Management:** Continuous risk evaluation helps reduce project uncertainty.
- **Flexibility:** Iterative development allows requirements to evolve during the project.
- **Suitability for Complex Projects:** The model performs well in large systems that involve significant technical uncertainty.

Nevertheless, the Spiral Model also has several disadvantages [32]:

1. **Implementation Complexity:** The model may be difficult to understand and manage.
2. **Higher Development Costs:** Risk analysis and iterative cycles may increase project costs.
3. **Requirement for Specialized Expertise:** Effective risk assessment requires experienced project managers and technical specialists.

3. Agile Software Engineering (Agile SE)

Agile Software Engineering represents a family of development methodologies that emphasize adaptability, collaboration, and rapid delivery of functional software. Frameworks such as **Scrum, Kanban, and Extreme Programming (XP)** are commonly categorized within the Agile approach [33].

Agile development is based on several key principles [34]:

- **Customer Satisfaction:** Continuous delivery of valuable software to meet user needs.
- **Adaptability to Change:** Requirements can evolve throughout the development process.
- **Frequent Delivery:** Working software is delivered in short development cycles (sprints or iterations).

- **Collaboration:** Close interaction between developers, stakeholders, and customers.
- **Iterative Development:** Systems are developed incrementally through repeated cycles.

The main advantages of Agile methodologies include [33]:

1. **High Flexibility:** Agile approaches adapt easily to changing requirements.
2. **Rapid Development:** Short development cycles accelerate software delivery.
3. **Strong Customer Collaboration:** Continuous user involvement improves alignment with actual needs.
4. **Early Problem Detection:** Frequent releases help identify issues earlier in the development process.

Despite these strengths, Agile methodologies also present some limitations [34]:

1. **Dependence on Customer Participation:** Active stakeholder involvement is required throughout development.
2. **Reduced Documentation:** Agile approaches often prioritize working software over extensive documentation.
3. **Challenges for Large Projects:** Managing large and complex systems using Agile alone can be difficult, although frameworks such as the **Scaled Agile Framework (SAF)** attempt to address this limitation.

A comparison of the main characteristics of the V-Model, Spiral Model, and Agile methodologies is presented in **Table 2.1**.

Table 2.1 Comparison of V-Model, Spiral Model, and Agile SE methodologies

Feature	V-Model	Spiral Model	Agile SE
Model Type	Linear, Sequential	Iterative, Risk-Driven	Iterative, Adaptive
Risk Management	Limited	Strong	Moderate
Flexibility	Low	High	Very High
Documentation	Extensive	Moderate	Limited
Development Speed	Low	Moderate	High
Suitable For	Stable Requirements	Complex Projects	Dynamic Projects
Customer Involvement	Limited	Moderate	Very High

The selection of an appropriate development methodology depends largely on the nature of the project, the stability of requirements, and the level of risk involved. The **V-Model** is generally suitable for projects with stable and well-defined requirements. The **Spiral Model** is more appropriate for complex systems where risk management is critical. In contrast, **Agile SE** is particularly effective for dynamic environments where requirements evolve and rapid delivery is essential.

2.2.2 Systems Engineering Management (SEM)

2.2.2.1 The Role of SEM in Guiding and Controlling SE Processes

Systems Engineering Management (SEM) plays a critical role in guiding and coordinating Systems Engineering (SE) activities throughout the system lifecycle. Unlike traditional project management, SEM requires a deeper understanding of engineering processes, system complexity, and the interactions between technical and organizational elements. A Systems Engineering Manager must therefore combine managerial skills with technical knowledge to effectively guide system development and ensure that project objectives are achieved.

To perform this role effectively, the SEM must be familiar with several theoretical and methodological foundations.

Systems Theory : A systems engineering manager should have a solid understanding of systems theory concepts such as complexity, emergence, feedback mechanisms, and dynamic system behaviour. These concepts help managers understand how different system components interact and how unexpected system behaviours may emerge during system operation [35].

Systems Modelling : Modern systems engineering increasingly relies on modelling techniques such as Systems Modelling Language (SysML), Model-Based Systems Engineering (MBSE), and enterprise architecture frameworks. These tools allow managers to visualize system structures, analyse relationships between components, and evaluate alternative design solutions [35].

Decision Theory : Decision-making in systems engineering often occurs under conditions of uncertainty. Therefore, SEMs must be familiar with decision theory approaches such as multi-criteria decision analysis (MCDA) and structured risk assessment methods in order to support rational and evidence-based decision-making processes [36].

Organizational Learning and Knowledge Management : Systems engineering projects generate large amounts of knowledge throughout the lifecycle. SEMs play an important role in promoting organizational learning by encouraging knowledge sharing, feedback mechanisms, and continuous improvement. Effective knowledge management practices help organizations capture lessons learned and reuse valuable engineering knowledge in future projects.

Beyond theoretical knowledge, SEMs are also responsible for managing several key engineering processes throughout the system lifecycle. These responsibilities typically include the following activities [37].

Requirements Management : SEMs must ensure that system requirements are clearly defined, documented, and continuously managed. This includes resolving ambiguous requirements using techniques such as goal modeling and conceptual modeling, as well as managing requirement changes through impact analysis and cost-benefit evaluation.

System Design Management : During the design phase, SEMs oversee architecture-centric system design. This involves ensuring that system architectures remain maintainable, scalable, and adaptable to future changes. Trade-off analysis is frequently conducted to evaluate alternative design solutions based on performance, cost, risk, and schedule considerations.

Implementation and Integration Management : At the implementation stage, configuration management becomes essential for controlling modifications to system artifacts such as code, documentation, and design models. Modern development environments also employ automation tools such as continuous integration and continuous delivery (CI/CD) pipelines to improve development efficiency and reduce integration errors.

Testing and Evaluation : Verification and validation activities must be carefully coordinated throughout the project lifecycle. Model-based testing techniques can be used to automatically generate test cases and evaluate system reliability. In addition, performance and reliability testing ensure that the system satisfies both functional and non-functional requirements.

Operation and Maintenance : After deployment, SEM activities continue during system operation and maintenance. Data collected during system operation can be analysed using advanced analytics and machine learning techniques to identify potential failures and improve system performance through continuous optimization.

2.2.2.2 Key SEM Processes: Planning, Organizing, Monitoring, and Controlling

To effectively guide systems engineering projects, SEM relies on four fundamental management processes: **planning, organizing, monitoring, and controlling** [20]. These processes form a continuous management cycle that supports the successful execution of complex engineering projects.

Planning

Planning represents the foundation of systems engineering management. At this stage, the SEM defines the project scope, objectives, and overall development strategy. Effective planning typically includes several key activities [38]:

- **Scope Definition:** Identifying project boundaries, stakeholders, and system objectives.
- **Work Breakdown Structure (WBS):** Decomposing the project into manageable tasks and deliverables.
- **Schedule Development:** Establishing project timelines and identifying dependencies between activities.
- **Budget Estimation:** Determining financial requirements for personnel, equipment, and other resources.
- **Risk Management Planning:** Identifying potential project risks and defining mitigation strategies.
- **Communication Planning:** Defining communication channels and reporting structures among stakeholders.
- **Quality Planning:** Establishing quality standards and assurance procedures throughout the project lifecycle.

Organizing

Following the planning stage, the SEM must organize the resources required to execute the project effectively. Organizing activities include team formation, resource allocation, and establishment of appropriate management structures [35].

These responsibilities typically involve defining roles and responsibilities, allocating financial and technical resources, establishing collaboration environments, and managing contracts with suppliers or external partners.

Monitoring

Monitoring focuses on tracking project progress and ensuring that activities are executed according to the project plan. The SEM collects performance data related to schedule, cost, quality, and risk levels. Monitoring activities typically include performance tracking, quality evaluation, deviation detection, and periodic reporting to stakeholders [39].

Controlling

Controlling involves implementing corrective actions when deviations from the project plan occur. SEM managers analyse root causes of problems and apply corrective measures such as adjusting schedules, reallocating resources, or revising project plans. Effective change management and continuous risk mitigation are essential components of this stage [27].

Together, these four processes form a continuous feedback loop. Planning establishes the project direction, organizing allocates resources, monitoring evaluates progress, and controlling ensures that corrective actions are taken when necessary. By continuously cycling through these stages, SEM helps maintain project alignment with technical requirements and organizational objectives.

Tools Supporting SEM Activities

Systems Engineering Managers frequently rely on specialized tools to support these processes. Common examples include:

- **Project Management Tools:** Microsoft Project, Jira, and Asana
- **Risk Analysis Tools:** @RISK and Palisade Decision Tools
- **Systems Modelling Tools:** Cameo Systems Modeler and Enterprise Architect
- **Collaboration Platforms:** Microsoft Teams and Slack

By combining structured management processes with appropriate tools and technical expertise, SEM plays a critical role in ensuring the successful execution of complex systems engineering projects.

2.2.2.3 The Importance of Optimizing SEM Processes to Improve Efficiency and Reduce Costs

Optimizing Systems Engineering Management (SEM) processes is not merely a matter of improving operational efficiency; it represents a strategic necessity for organizations operating in complex and rapidly changing environments. As modern systems become increasingly sophisticated and interconnected, organizations face growing competitive pressure and resource limitations. In such conditions, improving SEM processes can significantly enhance operational efficiency, reduce costs, and increase the overall value generated by engineering projects [40].

Several factors highlight the importance of optimizing SEM processes [41].

Reduction of Development Cycle Time. Inefficient SEM processes often lead to extended development and implementation cycles. By identifying bottlenecks, streamlining workflows, and introducing automation, organizations can shorten development timelines and accelerate time-to-market.

Cost Reduction. Poorly managed engineering processes may increase costs across multiple stages of the system lifecycle, including development, production, operation, and maintenance. Process optimization helps minimize rework, reduce errors, and eliminate unnecessary activities, ultimately improving the return on investment (ROI).

Improvement of System Quality. Well-optimized SEM processes enable earlier detection of errors and more effective quality control mechanisms. As a result, system reliability improves and the risk of operational failures is reduced.

Improved Decision-Making. Efficient management processes ensure that accurate and timely information is available to managers and engineers. Access to reliable data enables more informed and evidence-based decision-making.

Greater Organizational Agility. Optimized engineering processes allow organizations to respond more effectively to evolving customer needs, technological changes, and market dynamics.

Increased Customer Satisfaction. When systems are developed more efficiently and reliably, they are more likely to meet user expectations and operational requirements, ultimately improving customer satisfaction and long-term organizational reputation.

Approaches for Optimizing SEM Processes

Various methodologies and analytical approaches have been proposed to improve the efficiency of SEM processes [42].

Lean Systems Engineering. Lean principles can be applied to systems engineering activities in order to eliminate waste, streamline workflows, and improve value delivery throughout the system lifecycle.

Six Sigma for Systems Engineering. The Six Sigma methodology focuses on reducing process variability and minimizing defects. Techniques such as the DMAIC cycle (Define, Measure, Analyse, Improve, Control) are commonly used to improve engineering processes.

Model-Based Systems Engineering (MBSE). MBSE uses formal system models to support system analysis, design, and validation. By relying on structured models rather than fragmented documentation, MBSE improves communication between stakeholders and reduces development errors.

Process Mining. Process mining techniques analyse event data generated during system development activities to identify bottlenecks, inefficiencies, and opportunities for improvement.

Automation and Digitalization. Automating repetitive engineering activities—such as testing, configuration management, and documentation generation—can significantly improve productivity and reduce human error.

DevOps for Systems Engineering. DevOps principles promote collaboration between development and operational teams while supporting automated integration and deployment processes. This approach increases development speed and system reliability.

Systems Thinking and Complexity Science. Applying systems thinking allows organizations to better understand interactions between system components and identify opportunities for holistic optimization.

Value Stream Mapping (VSM). Value Stream Mapping is used to visualize engineering workflows, enabling managers to detect inefficiencies and improve value delivery across development processes.

Performance Indicators for Evaluating SEM Optimization

To assess the effectiveness of SEM optimization initiatives, organizations commonly rely on a set of **Key Performance Indicators (KPIs)** [43].

These indicators may include:

- **Development Cycle Time:** Time required to design, develop, and deploy a system.
- **Development Cost:** Total cost associated with system development activities.
- **Defect Rate:** Number of errors or defects detected during or after system development.
- **Customer Satisfaction Index:** Level of user satisfaction with system performance and reliability.
- **Productivity Metrics:** Measurement of engineering output relative to time or resource usage.
- **Project Success Rate:** Percentage of projects completed within schedule and budget constraints.
- **Return on Investment (ROI):** Financial benefits obtained through improved SEM processes.

Evaluating these indicators enables organizations to monitor the effectiveness of their engineering management strategies and continuously refine their development processes.

2.2.3 The Importance of Data and Artificial Intelligence

2.2.3.1 The Data Explosion and the Necessity of Advanced Analytics Tools

The term **“data explosion”** refers to the rapid and exponential growth in the volume, velocity, and diversity of data generated in modern digital environments. This phenomenon has been driven by technological advancements such as the Internet of Things (IoT), social media platforms, sensor networks, and widespread digitalization of business processes [44]. As organizations increasingly rely on data-driven decision-making, the ability to manage and analyze large volumes of data has become a critical organizational capability.

The data explosion is often described through the concept of the **“4Vs of Big Data,”** which has been extended in recent years to include additional characteristics [45].

Volume.
The quantity of data produced globally has increased dramatically, with organizations routinely generating and storing massive datasets measured in petabytes and even exabytes.

Velocity.
Data is generated and processed at high speeds, particularly in environments involving real-time sensor streams, online transactions, and digital communication platforms.

Variety.
Modern data exists in multiple formats, including structured data (databases), semi-structured data (logs and XML files), and unstructured data such as text, images, audio, and video.

Veracity.
Data may contain noise, inconsistencies, or uncertainty. Ensuring data accuracy and reliability is therefore a major challenge.

Additional dimensions often discussed include:

- **Value:** Extracting meaningful insights and economic value from large datasets.
- **Variability:** The dynamic and changing nature of data patterns over time.

Traditional data analysis tools—such as spreadsheets, basic database queries, and conventional business intelligence platforms—were originally designed for relatively small datasets. When confronted with the scale and complexity of modern data environments, these tools face several limitations.

These limitations include **limited scalability, reduced processing performance, restricted flexibility in handling unstructured data, and heavy reliance on manual analytical procedures**.

Consequently, organizations increasingly rely on **advanced data analytics technologies**, including machine learning algorithms, big data platforms, and artificial intelligence systems. These technologies allow organizations to extract meaningful insights from large and complex datasets, improve decision-making processes, and enhance operational efficiency.

The data explosion is therefore not only a technological challenge but also a strategic opportunity. Organizations that successfully adopt advanced analytical tools can transform raw data into actionable knowledge, enabling better decisions, improved efficiency, and stronger competitive advantage.

2.3 Background of the Research

Systems Engineering (SE) has long been recognized as an interdisciplinary approach for designing, developing, and managing complex systems. However, the increasing complexity of modern engineering systems, combined with growing volumes of operational data, has introduced new challenges related to uncertainty, risk management, and information processing. In recent years, advances in **data analytics and Artificial Intelligence (AI)** have created new opportunities for improving the efficiency and effectiveness of Systems Engineering processes. As a result, a growing body of research has explored how these technologies can support decision-making, risk management, system monitoring, and process optimization within SE environments.

One important area of research focuses on the use of **predictive analytics for risk management** in complex engineering projects. For example, predictive models based on machine learning techniques have been proposed to forecast project risks such as schedule delays and cost overruns. In one study, the Random Forest algorithm was applied to predict project delivery risks, achieving prediction accuracies of approximately 85% and enabling project managers to take proactive mitigation actions [46]. Such predictive approaches can significantly improve project planning and reduce the negative impact of unforeseen risks.

Another line of research investigates the application of **data mining techniques for identifying failure patterns** in complex systems. By applying clustering and classification algorithms to system data, researchers have been able to detect patterns associated with specific types of system failures. These insights allow engineers to anticipate potential faults before they occur and implement preventive measures, ultimately extending system lifespan and improving operational reliability [47].

Natural Language Processing (NLP) has also been explored as a tool for improving **requirements management** in systems engineering. Engineering projects often involve large volumes of textual documentation, such as technical specifications and requirement descriptions. NLP techniques can automatically extract relevant requirements from these documents, reducing manual effort and improving accuracy. Studies have reported that NLP-based approaches can reduce the time required for requirement extraction by up to 60%, while also reducing the likelihood of human error [48].

Machine learning techniques have further been applied to **optimize resource allocation** in engineering projects. Neural network models have been developed to analyze project constraints and recommend optimal allocations of financial and human resources. Experimental results demonstrate that such models can reduce project costs and shorten completion time by improving the efficiency of resource planning [49].

Artificial Intelligence has also been applied to evaluate **system performance throughout the system lifecycle**. Intelligent monitoring systems can automatically collect operational data, analyze system behavior, and generate performance reports for engineers and managers. These systems enable faster identification of operational issues and contribute to improved system quality and reliability [50].

In addition, **reinforcement learning** techniques have shown promising results in controlling complex systems such as transportation networks and energy systems. By learning optimal control strategies through interaction with system environments, reinforcement learning models can significantly improve system performance and operational efficiency [51].

Several studies have also demonstrated the benefits of combining **AI techniques with traditional system modeling approaches**. Integrating machine learning algorithms with system simulation models allows engineers to better predict system behavior and evaluate design alternatives before implementation. Research has shown that combining these methods can improve prediction accuracy by up to 25% compared with traditional modeling approaches alone [52].

Beyond technical system design, data analytics has also been applied to **systems engineering supply chain management**. Big data analytics techniques can help analyze supply chain data, identify inefficiencies, and optimize logistics operations. Empirical studies indicate that these approaches can reduce supply chain costs while improving delivery performance [53].

Other research has explored the use of **clustering algorithms for managing system requirements** by grouping similar requirements together. This approach can help identify conflicts among requirements and improve requirements organization during system development [54].

Artificial Intelligence has also been investigated as a tool for **automating engineering documentation**. Automated documentation systems use AI algorithms to generate technical documentation based on system data and design information. Studies report that such tools can reduce documentation preparation time while improving consistency and quality [55].

In the area of **customer feedback analysis**, sentiment analysis techniques have been applied to analyze user feedback and identify design improvements for engineering systems. By extracting insights from customer opinions, system designers can better understand user expectations and improve system usability [56].

AI-based tools have also been developed to assist engineers in **detecting software defects** and suggesting potential fixes. These tools can significantly reduce the number of coding errors and improve software quality during development [57]. Similarly, AI techniques have been applied in **system testing and validation**, where automated test case generation and evaluation can reduce testing time and cost while improving test coverage [58].

Security is another important area where data analytics plays a role. Data mining techniques have been used to detect **security vulnerabilities** in complex systems, enabling earlier identification of potential cyber threats and improving system security [59].

Natural Language Processing has also been applied to analyze **error reports and system logs**, allowing engineers to identify root causes of system failures more quickly and accurately [60]. In addition, AI-based configuration management systems have been proposed to manage system configurations and ensure compatibility between system components [61].

Researchers have further explored the integration of **AI techniques with simulation models** to evaluate alternative system scenarios. These combined approaches allow engineers to test multiple design options and identify optimal solutions before implementing changes in real-world systems [62].

Energy optimization has also been an important application area. AI-based optimization algorithms have been used to analyze energy consumption patterns and improve energy efficiency in complex systems [63]. Similarly, machine learning techniques have been applied to **predict system maintenance needs**, allowing organizations to implement predictive maintenance strategies and reduce maintenance costs [64].

Artificial Intelligence has also been used to support **decision-making processes in Systems Engineering Management**. Decision support systems based on AI can analyze large datasets and recommend optimal decisions, reducing decision-making time and improving management efficiency [65].

Time-series analysis techniques such as **ARIMA and Long Short-Term Memory (LSTM) networks** have also been used to predict changes in system parameters over time. Studies have shown that LSTM models often outperform traditional statistical methods when forecasting dynamic system behaviors [66].

Other applications include the use of AI to **optimize user interface design**, where machine learning algorithms analyze user behavior to recommend design improvements that enhance system usability and efficiency [67].

AI-based **anomaly detection techniques** have also been applied to sensor data to identify abnormal system behavior. Such methods can detect anomalies with high accuracy, enabling engineers to diagnose problems at early stages [68].

In addition, AI has been used to **automatically generate system status reports**, reducing the time required for reporting while improving the accuracy and consistency of information provided to stakeholders [69].

Finally, several studies have explored the integration of **Artificial Intelligence with Internet of Things (IoT) technologies** to develop self-organizing smart systems. These systems are capable of automatically responding to environmental changes and optimizing their performance through adaptive algorithms [70].

Overall, these studies demonstrate the growing potential of data analytics and AI techniques in improving various aspects of systems engineering, including risk prediction, failure detection, requirements management, resource optimization, system monitoring, and decision support. However, despite these promising developments, existing research remains dispersed across different application areas and lacks a comprehensive framework for understanding how AI technologies can systematically support Systems Engineering Management processes.

2.4 Chapter Summary

This chapter reviewed the theoretical foundations and research background related to **Systems Engineering (SE)**, **Systems Engineering Management (SEM)**, and the growing role of **data analytics and Artificial Intelligence (AI)** in improving engineering processes.

Systems Engineering was introduced as an interdisciplinary approach for designing, developing, and managing complex systems while ensuring that stakeholder requirements are satisfied. Key SE principles—including requirements definition, lifecycle thinking, risk management, and verification and validation—provide structured guidance for managing complex system development activities.

The concept of the **System Lifecycle (SLC)** was also discussed, highlighting the stages that systems pass through from initial concept to retirement. Several lifecycle development methodologies, including the **V-Model**, **Spiral Model**, and **Agile Systems Engineering**, were examined and compared. Each methodology provides different mechanisms for managing system complexity, addressing project risks, and supporting development flexibility. As a result, selecting an appropriate methodology depends largely on the specific characteristics and requirements of the project.

The chapter also examined the role of **Systems Engineering Management (SEM)** in guiding and coordinating engineering processes. Key managerial functions—such as planning, organizing, monitoring, and controlling—were described as essential activities for managing multidisciplinary engineering teams and ensuring that development activities remain aligned with project objectives. In this context, the importance of optimizing SEM processes to improve efficiency, reduce costs, and support better decision-making was highlighted.

Furthermore, the chapter discussed the growing importance of **data and Artificial Intelligence technologies** in modern engineering environments. The rapid increase in data generation, often referred to as the **"data explosion,"** has created new opportunities for applying advanced analytics and AI techniques to support engineering decision-making. Existing research shows that AI technologies can contribute to various systems engineering activities, including risk prediction, failure detection, requirements analysis, resource optimization, system monitoring, and predictive maintenance.

Despite these promising developments, the current literature remains fragmented across different application domains. Many studies focus on specific technical applications of AI rather than providing a comprehensive and systematic analysis of how AI techniques are integrated across Systems Engineering Management processes.

For this reason, a structured and systematic investigation of the existing literature is necessary to better understand how Artificial Intelligence and data analytics are applied within Systems Engineering Management. To address this need, the following chapter presents the research methodology used in this study, including the **Systematic Literature Review (SLR)** approach adopted to analyze and categorize existing research in this field.

3. Chapter 3 : Research Methodology

3.1 Introduction

This chapter presents the research methodology adopted in this study and explains the procedures used to collect, analyze, and synthesize the relevant literature. The aim of this chapter is to provide transparency in the research process and ensure that the study can be replicated and evaluated by other researchers.

Considering the nature of the research problem—investigating the role of Artificial Intelligence and data analytics in supporting Systems Engineering Management (SEM) processes—a **Systematic Literature Review (SLR)** was selected as the primary research method. The SLR approach offers a structured and transparent procedure for identifying, evaluating, and synthesizing existing research related to a specific topic.

Unlike traditional narrative literature reviews, systematic literature reviews follow a clearly defined and reproducible process for searching, selecting, and analyzing scientific publications. This structured approach helps reduce selection bias and ensures that the analysis is based on a comprehensive and representative set of studies.

The use of an SLR is particularly appropriate for this research because the intersection between Artificial Intelligence and Systems Engineering Management is a rapidly evolving and interdisciplinary field. Relevant studies are distributed across several research domains, including systems engineering, project management, data analytics, and artificial intelligence. A systematic review therefore allows the integration of knowledge from these different areas and supports the identification of research trends, technological applications, and existing research gaps.

The following sections describe the research methodology in detail, including the systematic literature review approach, search strategy, inclusion and exclusion criteria, study selection process, data extraction procedures, and methods used for analyzing and synthesizing the collected data.

3.2 Systematic Literature Review Approach

This research adopts a qualitative research design based on a **Systematic Literature Review (SLR)** methodology. By following predefined procedures and criteria, systematic reviews help ensure the reliability and reproducibility of the research process while minimizing potential selection bias.

The use of an SLR is particularly suitable for this study because the research topic—Artificial Intelligence and data analytics in Systems Engineering Management—extends across several academic disciplines, including systems engineering, data science, and project management. Conducting a systematic review enables the integration of knowledge from these diverse fields and facilitates the identification of technological trends, research contributions, and existing knowledge gaps.

3.2.1 Methodological Framework

The methodological framework used in this systematic literature review consists of several stages designed to ensure a structured and rigorous research process.

First, **inclusion and exclusion criteria** were defined to determine which studies were relevant to the objectives of the research. These criteria helped ensure that only high-quality and relevant publications were considered for analysis.

Second, a **structured search strategy** was developed to identify relevant studies across multiple academic databases. Carefully selected keywords and search strings were used to ensure broad coverage of the literature related to Artificial Intelligence and Systems Engineering Management.

Third, the selected studies were subjected to **content analysis and thematic coding**. Through this process, relevant information was extracted from each study and categorized according to themes related to the application of Artificial Intelligence in Systems Engineering Management.

Finally, the extracted data were **analyzed and synthesized** in order to identify patterns, research trends, and relationships between technologies and systems engineering processes. This structured analysis helped generate insights into how Artificial Intelligence and data analytics can contribute to improving Systems Engineering Management activities.

3.3 Scope of the Research

This section defines the boundaries of the systematic literature review and specifies the criteria used to select relevant studies for analysis. Establishing clear inclusion and exclusion criteria ensures that the review focuses on high-quality and relevant literature while maintaining transparency and consistency in the study selection process.

3.3.1 Inclusion Scope

The scope of the literature review was defined based on thematic relevance, publication period, and language.

Thematic Scope

The review focuses on studies examining the application of emerging technologies for improving Systems Engineering Management (SEM) processes. Particular attention is given to Artificial Intelligence and advanced data analytics technologies, including machine learning, deep learning, neural networks, and other data-driven techniques used to support decision-making, risk management, system monitoring, and process optimization.

Temporal Scope

To capture recent developments and technological advancements in this field, studies published between **2014 and 2025** were considered.

Language Scope

Studies published in **English and Persian** were included to incorporate both international and regional research contributions.

3.3.2 Inclusion Criteria

Studies were included in the review if they met the following criteria:

- The study examines the application of Artificial Intelligence, data analytics, or related technologies within the context of Systems Engineering or Systems Engineering Management.
- The study provides empirical analysis, practical applications, case studies, or systematic review results.
- The publication is a peer-reviewed journal article, conference paper, or scientifically validated research report.

3.3.3 Exclusion Criteria

Studies were excluded if they met any of the following conditions:

- The study does not address Systems Engineering or Systems Engineering Management processes.

- The research focuses on emerging technologies without clear relevance to engineering management or system lifecycle processes.
- The publication lacks empirical analysis, methodological rigor, or scientific credibility.
- The source is non-peer-reviewed or lacks sufficient academic reliability.

3.4 Systematic Review Process

This study followed a structured **Systematic Literature Review (SLR)** protocol to ensure transparency, replicability, and methodological rigor. The review process consisted of four main stages:

1. Systematic search
2. Screening and study selection
3. Data extraction
4. Qualitative synthesis

3.4.1 Systematic Search

A keyword-based search strategy was developed to identify studies related to the application of Artificial Intelligence and data analytics in Systems Engineering Management (SEM). Search queries were constructed using combinations of terms related to both **Systems Engineering Management** and **emerging technologies**.

Example search strings included:

- (“systems engineering” OR “systems engineering management” OR SEM OR SEMP) AND (“artificial intelligence” OR AI OR “machine learning” OR “deep learning” OR NLP)

- (“systems engineering” OR “systems engineering management” OR SEM OR SEMP) AND (“data analytics” OR “big data” OR “process mining” OR “predictive analytics”)

Additional terms such as **digital twin** and **digital transformation** were also included when relevant to the defined research scope.

The literature search was conducted using the following databases:

- Scopus
- Web of Science

- IEEE Xplore
- Google Scholar (used as a supplementary source to identify potentially missing studies)
- Persian scientific databases including **SID** and **MagIran**.

3.4.2 Screening and Study Selection

The selection process was carried out in several stages to ensure that only relevant and high-quality studies were included.

First, **duplicate records were removed** after merging search results from all databases using reference management software (EndNote).

Second, the remaining studies were screened based on **titles and abstracts**. Articles that were clearly unrelated to Systems Engineering Management or AI/data analytics applications were excluded.

Third, the **full texts of the remaining articles** were reviewed to confirm their relevance and compliance with the defined inclusion and exclusion criteria.

All screening decisions and study metadata were recorded in EndNote to ensure transparency and traceability in the selection process.

3.4.3 Data Extraction

For each included study, a structured data extraction form was used to collect relevant information. The extracted data included:

- Publication metadata (year, venue, and research domain)
- Targeted SEM or SEMP process or lifecycle stage
- Applied AI or data analytics techniques (e.g., machine learning, deep learning, NLP, optimization, process mining)
- Data sources used (e.g., requirements documents, logs, sensor data, project records, test reports)
- Reported objectives and outcomes (e.g., prediction, classification, anomaly detection, decision support)
- Limitations and challenges identified by the authors

These variables were selected to support the thematic synthesis and the maturity analysis conducted in later chapters.

3.4.4 Data Analysis and Synthesis

The selected studies were analysed using **thematic content analysis**. The analysis followed several steps.

First, **initial coding** was performed by identifying relevant text segments and assigning codes related to the research questions and extracted data fields.

Second, the codes were grouped into **higher-level thematic categories** representing the major application areas of Artificial Intelligence and data analytics within Systems Engineering Management.

Third, relationships between these themes were examined in order to identify patterns and concentrations in the literature, such as the relationship between specific AI techniques and SEM processes.

Finally, the synthesized findings were used to address the research questions, identify research gaps, and support the development of the **AI-SEM maturity framework** presented in later chapters.

3.5 Validation and Data Quality Assurance

To ensure the validity and reliability of the collected data and the resulting findings, several quality assurance measures were implemented throughout the research process.

First, only **peer-reviewed and scientifically credible publications** were included in the final dataset to maintain academic quality.

Second, multiple rounds of review were conducted during the screening and analysis stages to reduce the risk of selection errors and improve consistency in the interpretation of results.

In addition, a structured thematic content analysis framework was used to ensure consistency in coding and categorization of the selected studies. Where necessary, consultations with supervisors and subject-matter experts were conducted to verify interpretations and strengthen the robustness of the analysis.

3.6 Study Selection Results

Following the systematic search protocol across the selected academic databases, a total of 141 articles were initially identified. These records represent the preliminary dataset retrieved using the defined search strategy described in Section 3.3.

During the first screening stage, which involved reviewing the titles and abstracts of the retrieved publications, 39 articles were excluded because they did not meet the relevance criteria established for this study. As a result, 102 studies were considered potentially relevant to the research topic and were selected for further evaluation.

Subsequently, a full-text review was conducted based on the inclusion and exclusion criteria defined in Section 3.3. During this stage, 29 additional articles were excluded due to factors such as lack of relevance to Systems Engineering Management, insufficient discussion of Artificial Intelligence or data analytics applications, or limited scientific rigor.

After completing the eligibility assessment, 73 articles met the inclusion criteria and were retained in the final dataset for analysis. The overall study selection process is illustrated in Figure 3.X, which presents the PRISMA flow diagram summarizing the identification, screening, eligibility assessment, and final inclusion of studies in this systematic literature review.

Detailed information about the selected studies—including publication year, authors, article title, technology domain, and key findings—is presented in Table 4.1.

To facilitate the analysis of research evolution, the selected studies are organized chronologically in Table 4.1, beginning with the most recent publications and proceeding toward earlier studies. This arrangement helps illustrate research trends, methodological developments, and emerging technological applications within Systems Engineering Management.

The overall study selection process is illustrated in Figure 3.X, which presents the PRISMA flow diagram summarizing the identification, screening, eligibility assessment, and final inclusion of studies in this systematic literature review

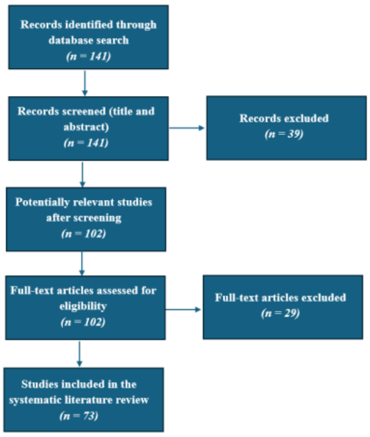

Figure 3.1PRISMA Flow Diagram

3.7 Methodological Limitations

Despite the rigorous methodology applied in this research, several limitations should be acknowledged.

First, access limitations may have prevented the inclusion of some relevant publications or industry reports that were not available through the selected databases.

Second, the review was limited to **English and Persian publications**, which may have excluded potentially relevant studies published in other languages.

Third, although the systematic review protocol was carefully designed, **researcher interpretation** may still influence the classification and analysis of the selected studies.

Finally, given the rapid development of Artificial Intelligence and data analytics technologies, new research may emerge after the completion of the literature review, which could influence the comprehensiveness of the findings.

4. Chapter 4 : Analysis and Evaluation of Selected Studies

4.1 Introduction

This chapter presents the analysis and evaluation of the studies selected through the systematic literature review described in Chapter 3. The analysis is based on a final dataset of **73 peer-reviewed articles** that examine the application of Artificial Intelligence and data analytics in **Systems Engineering Management (SEM)** processes.

The objective of this chapter is to synthesize the findings of these studies and identify major technological trends, application domains, and research patterns related to the use of AI and data-driven techniques in engineering systems management.

To achieve this objective, the selected studies are first summarized to provide an overview of the literature. Subsequently, the studies are analyzed according to several dimensions, including the technologies applied, the targeted Systems Engineering Management processes, and the main outcomes reported in the literature.

The findings presented in this chapter provide the analytical foundation for the discussion and interpretation developed in the following chapters.

4.2 Overview of Selected Studies

4.2.1 Purpose

The purpose of this section is to present a structured overview of the studies included in the systematic literature review. This overview provides a clear summary of the selected research and allows readers to quickly understand the scope of the analyzed literature.

To support transparency and traceability, key information from each study is summarized in **Table 4.1**. The table includes essential descriptive information about each article and serves as the primary dataset for the analysis conducted in this chapter.

4.2.2 Description of the Summary Table

Table 4.1 presents a summary of the **73 selected articles** included in this systematic literature review. For each study, the table reports the **author(s) and publication year, application domain, AI technique used, data type, and key contribution**.

The **author(s)/year** column identifies each study and shows the chronological development of the research area. The **domain** column indicates the field in which the AI application was studied, such as manufacturing, supply chain, energy systems, construction management, and project management. The **AI technique** column shows the main artificial intelligence methods applied in each study, while the **data type** column identifies the kind of data used, such as operational, sensor, project, or communication data. Finally, the **key contribution** column summarizes the main result or practical value of each study.

The articles are organized chronologically, beginning with the most recent publications, in order to illustrate the evolution of research trends and AI applications over time. Table 4.1 provides the foundation for the analytical discussion presented in the following sections of this chapter.

Table 4.1Summary of Selected Articles

Author(s)/ year	Domain	AI Technique	Data Type	Key Contribution
1. Kilari [71] (2025)	Manufacturing / Supply Chain	Machine Learning, Predictive Analytics	Operational Data	AI improves MES and supply chain efficiency through predictive maintenance, monitoring, and inventory optimization.
2. Alhamrouni et al. [72] (2024)	Energy Systems	Deep Learning, ML, Reinforcement Learning	Sensor Data	AI enhances power system stability through fault detection, predictive maintenance, and real-time monitoring.

3. Kilari [73] (2022)	Manufacturing	ML, Computer Vision, Predictive Analytics	Operational Data	AI reduces human errors and improves response time in MES and supply chain ordering systems.
4. Obiuto et al. [74] (2024)	Construction Management	Machine Learning, Predictive Analytics	Project Data	AI improves scheduling, risk management, and cost control in construction projects.
5. Kumari et al. [75] (2023)	Supply Chain	Machine Learning, Big Data Analytics	Supply Chain Data	AI enhances demand forecasting and decision-making in supply chain optimization.
6. Joshi [76] (2024)	Project Management	Natural Language Processing, AI Chatbots	Communication Data	AI chatbots improve stakeholder communication and engagement in project management through automated and real-time responses.
7. Zabala-Vargas et al. [77] (2023)	Construction / Project Management	Big Data Analytics, Machine Learning	Project Data	AI and big data analytics enhance project management in the AEC industry by improving prediction, planning, risk identification, and decision-making.
8. Stecyk et al.[78] (2023)	Energy Systems	Machine Learning, Multi-Criteria Decision Methods	Energy System Data	AI supports collaborative energy optimization by improving energy generation, distribution, and consumption planning.
9. Ohalete et al.[79] (2023)	Oil & Gas Industry	Machine Learning, Predictive Analytics	Operational Data	AI improves predictive maintenance in oil and gas systems by enabling early failure prediction and optimized maintenance scheduling.

10. Koshy et al. [80] (2021)	Smart Grid / Energy Systems	Machine Learning, Big Data Analytics	Sensor Data	AI and big data analytics enhance smart grid monitoring, energy forecasting, and decision-making using high-resolution operational data.
11. Jenis et al. [81] (2023)	Mechanical Engineering	Machine Learning, Deep Learning	Engineering Design Data	AI techniques improve mechanical design optimization and support automated engineering analysis.
12. Ekundayo [82] (2024)	Systems Engineering	Deep Learning, Reinforcement Learning, Digital Twin	System Data	AI-driven decision intelligence improves system optimization, predictive analysis, and operational efficiency in complex engineering systems.
13. Dalal et al. [83] (2020)	Healthcare / Pandemic Management	Artificial Intelligence, Data Analytics	Health Data	AI supports pandemic management through disease monitoring, prediction, and prevention strategies.
14. Hu et al. [84] (2024)	Civil Engineering	Multi-Criteria Decision Methods, AI Analytics	Project Data	AI-based decision models improve cost management and risk analysis in civil engineering projects.
15. Parekh [85] (2024)	Civil Engineering / Construction	Machine Learning, Genetic Algorithms	Infrastructure / Project Data	AI improves design analysis, infrastructure monitoring, and risk assessment in civil engineering projects.
16. Antwi & Avickson [86] (2024)	Enterprise Management	Machine Learning, Data Analytics	Enterprise Data	AI integration with SAP systems improves enterprise decision-making, process automation, and operational efficiency.
17. Solanki [87] (2024)	Oil & Gas Industry	Machine Learning, Data Analytics	Operational Data	AI and data analytics improve operational efficiency through predictive maintenance and data-driven decision-making.
18. Parthiban et al. [88] (2023)	Biotechnology / Systems Engineering	Machine Learning, Deep Learning	Biological / Experimental Data	AI supports protein design optimization and improves production efficiency in plant-based biopharmaceutical systems.

19. Das [89] (2021)	Software Engineering	Machine Learning, Natural Language Processing, Reinforcement Learning	Software Development Data	AI enhances software engineering processes through automation, defect prediction, and improved resource allocation.
20. Al Bashar & Khan [90] (2024)	Industrial Engineering	Machine Learning, Predictive Analytics	Industrial Operational Data	AI improves industrial engineering processes including production optimization, maintenance planning, and supply chain management.
21. Thilagavathy & Venkatasamy [91] (2023)	Business Management	Machine Learning, Predictive Analytics	Business / Organizational Data	AI improves strategic decision-making, operational efficiency, and customer relationship management in business organizations.
22. Bushuev [92] (2024)	IT Infrastructure Management	Machine Learning, Predictive Analytics	IT System Data	AI enables proactive monitoring and predictive maintenance to improve IT infrastructure reliability and reduce downtime.
23. Pentyala [93] (2024)	Data Engineering / Cloud Systems	Machine Learning, Deep Learning, Reinforcement Learning	System Logs / Operational Data	AI enables automated fault detection and failure prediction in cloud-based data engineering systems.
24. Helo & Hao [94] (2021)	Operations Management / Supply Chain	Machine Learning, AI Analytics	Supply Chain Data	AI improves supply chain operations through predictive decision-making and automated process optimization.
25. Kibria et al. [95] (2018)	Wireless Networks / Communication Systems	Machine Learning, Big Data Analytics	Network Data	AI enables intelligent and predictive management of next-generation wireless networks.
26. Alam et al. [96] (2021)	Environmental Engineering / Water Treatment	Machine Learning, AI Modeling	Environmental Data	AI models optimize water treatment processes and improve pollutant adsorption prediction.
27. Ribeiro et al. [97] (2021)	Industry 4.0 / Business Process Automation	Artificial Neural Networks, NLP, Text Mining	Business Process Data	AI-enhanced robotic process automation improves business process automation and decision-making.

28. Mwangi [98] (2024)	Supply Chain Management	Machine Learning, Predictive Analytics	Supply Chain Data	AI improves demand forecasting and inventory management for supply chain optimization.
29. Goswami et al. [99] (2025)	Supply Chain Management	Machine Learning, AI Analytics	Supply Chain Data	AI enhances supply chain agility and efficiency through predictive analytics and automation.
30. Hernandez et al. [100] (2024)	Sustainable Agriculture / Waste Management	Machine Learning, Data Analytics	Environmental Data	AI improves agricultural productivity and waste management through resource optimization and predictive monitoring.
31. Bhima et al. [101] (2023)	Management Information Systems	Machine Learning, Predictive Analytics	Organizational Data	AI improves organizational efficiency through automation and data-driven decision-making.
32. Dhamija [102] (2020)	Operations Management	AI, Genetic Algorithms, Big Data Analytics	Organizational Data	AI supports operational optimization and technology-driven decision-making in business environments.
33. Decardi-Nelson et al. [103]	Process Systems Engineering	Generative AI, Large Language Models	Engineering System Data	Generative AI enhances system design, optimization, and monitoring in process systems engineering.
34. Odunaiya et al. [104] (2022)	Renewable Energy Systems	Machine Learning, Predictive Analytics	Energy System Data	AI optimizes renewable energy production, forecasting, and grid management.
35. Bhagat & Kanyal [105] (2023)	Healthcare Management	Machine Learning, AI Analytics	Healthcare Data	AI improves hospital management efficiency and patient care through intelligent decision support.
36. Tarawneh et al. [106] (2021)	Project Management	Deep Neural Networks	Project Data	AI predicts project success and supports resource optimization in project management.
37. Guttha [107] (2024)	Technology Engineering	AI Analytics	Technology Data	Emerging AI-driven technologies support innovation and operational transformation in commercial systems.

38. Pal et al. [108] (2023)	Project Management	Machine Learning, Predictive Analytics	Project Data	AI improves project forecasting, risk assessment, and resource allocation.
39. Gadde [109] (2024)	Database Systems / Data Infrastructure	Machine Learning, AI Analytics	Database System Data	AI improves database performance through query optimization and anomaly detection.
40. Munagandla [110] (2024)	Higher Education Management	Machine Learning, Predictive Analytics	Research Management Data	AI improves research proposal evaluation and administrative decision-making processes.
41. Umeorah et al. [111] (2024)	Financial Management	Machine Learning, NLP	Financial Data	AI improves working capital management through predictive financial analysis.
42. Peralta et al. [112] (2025)	Enterprise Operations Management	NLP, Optimization Algorithms	Operational Data	AI-driven incident management improves response time and resource utilization in enterprise systems.
43. Arinze et al. [113] (2024)	Oil & Gas Engineering	Machine Learning, Predictive Analytics	Operational Data	AI enhances operational efficiency, predictive maintenance, and safety in oil and gas operations.
44. Adeyeye & Akanbi [114] (2024)	Systems Engineering	Optimization Algorithms, Machine Learning	System / Performance Data	Data analytics and optimization algorithms improve efficiency and decision-making in systems engineering processes.
45. Manchana [115] (2022)	Real Estate Project Management	Machine Learning, Deep Learning	Project Data	AI improves real estate project management through predictive analysis, risk management, and quality control.
46. Agarwal et al. [116] (2024)	Data Management	Artificial Intelligence, Machine Learning	Data Pipeline / Big Data	AI optimizes data pipelines through automation, data integration, and real-time decision support.
47. Upadhyaya [117] (2024)	Web Development	NLP, Machine Learning, Computer Vision	User / Web Data	AI enhances web development through automation, personalization, and improved decision-making.

48. Shishmanov & Marinova-Kostova [118] (2014)	Digital Transformation	Application Integration, SOA	Organizational Data	Application integration supports digital transformation by improving process efficiency and system flexibility.
49. Binder et al. [119] (2022)	Industry 4.0 / Production Systems	Artificial Intelligence, MBSE	Production / Big Data	AI-enabled information architecture improves investigation and optimization of flexible production systems.
50. Lins et al. [120] (2021)	AI Service Systems	Artificial Intelligence as a Service	Cloud / Service Data	AI-as-a-Service enables scalable AI adoption by reducing implementation complexity and improving accessibility.
51. Jakubik et al. [121] (2024)	Data-Centric AI	Data-Centric Artificial Intelligence	Structured / System Data	Data-centric AI improves system performance by prioritizing data quality and systematic dataset refinement.
52. Al Houri et al. [122] (2024)	Structural Engineering	Artificial Intelligence, Machine Learning	Structural / Monitoring Data	AI improves design optimization, structural monitoring, and sustainability in passive control structures.
53. Rane [123] (2024)	Renewable Energy	ChatGPT, Generative AI	Energy Data	Generative AI supports renewable energy modeling, forecasting, and optimization for sustainable energy systems.
54. Rane [124] (2023)	Construction Industry	ChatGPT, Generative AI	Construction / BIM Data	Generative AI improves construction processes through task automation, decision support, and process optimization.
55. Rane [125] (2023)	Business Management	ChatGPT, Large Language Models	Business / Customer Data	Large language models improve business operations through automation, data-driven decision-making, and process support.
56. Rane [126] (2024)	Industry 4.0 / Society 5.0	ChatGPT, Generative AI	Industrial / Social Data	Generative AI enhances productivity, human-machine collaboration, and smart industry development.

57. Rane [127] (2024)	Architectural Engineering	ChatGPT, Generative AI	Design / BIM Data	Generative AI supports architectural engineering through improved design efficiency, safety, and sustainability.
58. Rane [128] (2023)	AEC Industry	Artificial Intelligence, IoT, Big Data	Construction / Sensor Data	AI, IoT, and big data integration improves resource management and decision-making in the AEC industry.
59. Rane [129] (2023)	Smart Construction Management	BIM, Artificial Intelligence	Project / BIM Data	BIM-AI integration improves construction scheduling, cost, quality, and safety management.
60. Rane et al. [130] (2023)	AEC Industry	Artificial Intelligence, IoT Sensors	Sensor / Construction Data	AI-enabled IoT sensors improve real-time monitoring, predictive maintenance, and safety in the AEC sector.
61. Martins [131] (2024)	Business Operations	Artificial Intelligence	Business / Customer Data	AI improves business operations through analytics, risk management, personalization, and decision support.
62. Pokala [132] (2024)	ERP Systems	Artificial Intelligence, Adaptive Analytics	Enterprise Data	AI enhances ERP systems through automation, intelligent analytics, and improved organizational decision-making.
63. Venkataramanan et al. [133] (2025)	IT Operations	AIOps, Machine Learning	IT Logs / Operational Data	AIOps improves IT service management through anomaly detection, predictive maintenance, and automated root cause analysis.
64. Islam [134] (2024)	Database Management / Big Data	Machine Learning, Artificial Intelligence	Database / Big Data	AI and ML improve SQL databases and big data systems through query optimization, prediction, and security enhancement.
65. Pshichenko [135] (2024)	Project Management	Machine Learning, NLP, Neural Networks	Project Data	AI models improve project management through better decision-making, forecasting, and resource utilization.

66. Eyo-Udo [136] (2024)	Supply Chain Management	Machine Learning, Robotics	Supply Chain Data	AI improves supply chain efficiency through forecasting, logistics optimization, and resource management.
67. Elumilade et al. [137] (2023)	Financial Risk Management	Machine Learning, Predictive Analytics	Financial Data	Data analytics improves financial risk assessment, fraud detection, and strategic decision-making.
68. Shamim [138] (2024)	Project Management	Artificial Intelligence, Predictive Analytics	Project Data	AI improves project planning, resource allocation, and risk management to enhance project performance.
69. Devarasetty [139] (2024)	Data Engineering / Predictive Analytics	Random Forest, Machine Learning	Financial Data	Advanced data engineering improves predictive analytics accuracy and financial forecasting performance.
70. Marks & Spencer [140] (2025)	Mechanical Systems Engineering	Machine Learning, Evolutionary Algorithms	Engineering System Data	Computational AI techniques improve mechanical system optimization, diagnostics, and engineering decision-making.
71. Ajirotutu [141] (2024)	Construction Project Management	Artificial Intelligence, Predictive Analytics	Construction Data	AI enhances lean construction by improving resource optimization, workflow efficiency, and sustainability.
72. Arjunan (Accenture) [142] (2023)	Industrial Operations / Industry 4.0	Artificial Intelligence, Big Data, IoT	Industrial Data	AI-driven Industry 4.0 technologies enable predictive maintenance, automation, and optimized industrial operations.
73. Al Bashar [143] (2024)	Supply Chain / Inventory Management	Artificial Intelligence, Machine Learning	Supply Chain Data	AI improves inventory management through predictive analytics and optimized supply chain operations.

The summary presented in **Table 4.1** provides an overview of the 73 studies selected for this systematic literature review. The table highlights the diversity of research topics, technological approaches, and application domains in which

Artificial Intelligence and data analytics have been applied within Systems Engineering Management contexts.

A review of the selected studies shows that Artificial Intelligence technologies are increasingly used across multiple engineering and management domains, including supply chain management, energy systems, construction and infrastructure management, manufacturing systems, and project management. The studies collectively demonstrate that AI-based approaches are primarily applied to improve operational efficiency, support predictive analysis, optimize resource allocation, and enhance decision-making processes.

In addition, the selected studies employ a wide range of analytical techniques such as machine learning, deep learning, predictive analytics, natural language processing, and big data analytics. These technologies are often applied to analyze large volumes of operational, historical, sensor, or textual data to generate insights that support engineering management decisions.

While Table 4.1 provides a descriptive overview of the selected literature, a deeper analytical understanding requires organizing the studies according to common characteristics and research dimensions. Therefore, the selected articles were further coded according to their application domain, techniques used, data types, and key research outcomes. The results of this coding process are presented in **Table 4.2**, which forms the basis for the analytical discussion in the following sections.

4.3 Coding of the Selected Studies

In order to facilitate a systematic analysis of the literature, the selected studies were coded according to several analytical dimensions. This coding process allows the research to move beyond a descriptive listing of articles and instead identify patterns and relationships across the reviewed studies.

The coding framework was developed based on the key objectives of the research and the major variables relevant to the application of Artificial Intelligence and data analytics in Systems Engineering Management processes. Each study was examined and categorized according to its application domain, the techniques used, the types of data employed, and the main outcomes reported.

Through this coding approach, the diverse body of literature was organized into a structured dataset that enables comparison between studies and facilitates the identification of common technological trends and research directions. The coding process also helps highlight the areas where Artificial Intelligence technologies are most frequently applied, as well as the types of data and analytical methods used to support decision-making in engineering management contexts.

The results of this classification process are presented in Table 4.2, which summarizes the coding of the selected articles across the defined analytical categories. This table provides the foundation for the descriptive and analytical discussions presented in the following sections of this chapter.

Table 4.2 Coding of Article Content

Area of Application	Technique Used	Type of Data	Main Results	Description
1. Supply Chain Management, Manufacturing Systems	Machine Learning	Operational Data, Sensor Data	Improved demand forecasting, inventory optimization, predictive maintenance, cost reduction	Demonstrates how AI improves efficiency and reduces operational costs in manufacturing and supply chain systems.
2. Energy Systems	Machine Learning, Deep Learning, Reinforcement Learning	Sensor Data, Operational Data	Fault detection, predictive maintenance, improved system stability	Reviews AI applications for improving monitoring, control, and stability in power systems.
3. Construction Risk Management	Machine Learning, Predictive Analytics	Historical Data, Operational Data	Early risk identification, improved safety, reduced incident costs	Shows how AI can support risk management in construction projects.
4. Construction Management	Data Analytics, Machine Learning	Historical Data, Project Data	Improved planning and scheduling, increased efficiency, reduced project costs	Demonstrates AI applications for optimizing project planning and risk management in construction.

5. Supply Chain Management	Machine Learning, Big Data Analytics	Historical Data, Operational Data	Improved demand forecasting, supply chain optimization	Shows how AI enhances supply chain decision-making and operational performance.
6. Project Management	Natural Language Processing, AI Chatbots	Textual Data, Communication Data	Improved stakeholder communication, faster response time	Demonstrates how AI chatbots improve stakeholder engagement in project management.
7. Construction, Project Management (AEC Industry)	Big Data Analytics, Machine Learning	Research Data, Industry Data	Improved project forecasting, planning optimization	Reviews emerging technologies supporting project management in the AEC industry.
8. Energy Systems Optimization	Machine Learning, MCDM, Fuzzy AHP, TOPSIS	Energy System Operational Data	Improved energy management and system optimization	Demonstrates AI's role in optimizing energy generation and distribution systems.
9. Oil and Gas Industry	Machine Learning, Data Science	Sensor Data, Maintenance Data	Predictive maintenance, reduced downtime	Reviews AI applications improving maintenance strategies in oil and gas systems.
10. Smart Grid Systems	Big Data Analytics, Machine Learning	AMI Data, PMU Data	Improved power flow prediction and grid monitoring	Demonstrates AI applications for improving smart grid performance and reliability.
11. Mechanical Engineering Design	Machine Learning, Deep Learning	Design Data, Performance Data	Improved design optimization and component performance	Reviews AI applications for mechanical component design and engineering optimization.

12. Complex Industrial Systems	Deep Learning, Reinforcement Learning, Digital Twin	Operational Data, Simulation Data	Improved operational efficiency and system resilience	Demonstrates how AI supports intelligent decision-making in complex industrial systems.
13. Public Health, Pandemic Management	Machine Learning, Big Data Analytics	Medical Data, Epidemiological Data	Improved disease monitoring and response planning	Shows how AI supports pandemic analysis and public health decision-making.
14. Civil Engineering Cost Management	MCDM, ISM, MICMAC	Project Data, Expert Survey Data	Identification of key AI factors affecting project cost management	Provides a framework for improving cost management in construction projects using AI techniques.
15. Civil Engineering and Urban Infrastructure	Machine Learning, Genetic Algorithms	Design Data, Construction Data	Improved infrastructure design and defect detection	Reviews AI applications for optimizing construction planning and infrastructure maintenance.
16. Enterprise Management Systems (SAP)	Machine Learning, Artificial Intelligence	Enterprise System Data	Process automation and improved operational efficiency	Demonstrates how AI integration enhances enterprise resource planning and business management.
17. Oil and Gas Operations	Machine Learning, Data Analytics	Exploration and Production Data	Improved safety, predictive maintenance, operational efficiency	Shows how AI-driven analytics enhance operational performance in oil and gas industries.

18. Biotechnology and Molecular Engineering	Machine Learning, Deep Learning	Biological Data, Protein Data	Improved protein structure optimization and production efficiency	Demonstrates AI applications in biotechnology and pharmaceutical production systems.
19. Software Engineering Systems	Machine Learning, NLP, Reinforcement Learning	Code Data, Requirements Data	Automated development processes and improved defect prediction	Shows how AI improves software development efficiency and reliability.
20. Industrial Engineering Systems	Machine Learning, Predictive Analytics	Process Data, Supply Chain Data	Process optimization and improved operational productivity	Reviews AI applications for improving efficiency in industrial engineering systems.
Area of Application	Technique Used	Type of Data	Main Results	Description
21. Business Management	Data Analytics, Predictive Modeling, Automation	Customer Data, Supply Chain Data, Market Data	Improved decision-making, customer interaction, operational efficiency, strategic planning	Demonstrates how AI-driven analytics improves business decision-making and organizational performance.
22. IT Infrastructure Management	Proactive Analytics, Real-time Data Analytics, Anomaly Detection, Predictive Maintenance	System Performance Data, Log Data	Reduced downtime, improved resource allocation, operational cost reduction	Shows how AI-based proactive monitoring improves IT infrastructure reliability and efficiency.

23. Cloud Data Engineering Systems	Machine Learning, Deep Learning, Reinforcement Learning	System Data, Log Data	Automated fault detection, failure prediction, system reliability improvement	Demonstrates AI techniques for monitoring and fault detection in cloud-based data systems.
24. Supply Chain Management	Artificial Intelligence, Internet of Things (IoT)	Supply Chain Data, Sensor Data	Predictive supply chain management, automation, improved operational efficiency	Shows how AI combined with IoT enables proactive and intelligent supply chain management.
25. Next-Generation Wireless Networks	Big Data Analytics, Machine Learning, Artificial Intelligence	Network Data, Performance Data	Intelligent network optimization, predictive monitoring	Demonstrates how AI enhances performance and adaptability in wireless communication networks.
26. Water Treatment and Desalination	Artificial Intelligence, Machine Learning	Environmental Data, Chemical Data	Process optimization, improved pollutant removal prediction	Shows how AI improves efficiency and sustainability in water treatment systems.
27. Industry 4.0 Process Automation (RPA)	Artificial Neural Networks, Natural Language Processing	Business Process Data	Improved process automation, data extraction and classification	Demonstrates how AI enhances robotic process automation and operational efficiency in Industry 4.0.
28. Supply Chain Optimization	Machine Learning, Artificial Intelligence	Supply Chain Data	Improved demand forecasting, inventory optimization	Shows how AI techniques improve supply chain decision-making and performance.

29. Supply Chain Management	Artificial Intelligence	Demand Data, Inventory Data	Increased supply chain agility, cost reduction, improved customer experience	Demonstrates how AI enhances supply chain competitiveness and sustainability.
30. Sustainable Agriculture and Waste Management	Artificial Intelligence, Machine Learning	Agricultural Data, Weather Data, Waste Data	Increased productivity, improved resource efficiency, reduced emissions	Shows how AI supports sustainable agricultural practices and waste management.
31. Management Information Systems	Artificial Intelligence, Predictive Analytics, Automation	Organizational Data, Historical Data	Task automation, improved decision-making, increased operational efficiency	Demonstrates the role of AI in improving productivity through intelligent information systems.
32. Technology Management and AI Research Trends	Bibliometric Analysis, Clustering	Scientific Publication Data	Identification of major AI research themes and technological trends	Provides bibliometric insights into AI research development and application areas.
33. Process Systems Engineering	Generative AI, Large Language Models, Foundation Models	Engineering Research Data	Improved system design, process optimization, enhanced control	Reviews how generative AI can enhance modeling and optimization in process systems engineering.
34. Renewable Energy Systems	Machine Learning, Predictive Analytics, Data-driven Modeling	Energy Production and Consumption Data	Improved energy forecasting and optimized resource management	Demonstrates how AI supports efficient management of renewable energy systems.

35. Hospital Management	Artificial Intelligence	Administrative Data, Clinical Data	Improved patient management, increased operational efficiency	Explores the role of AI in improving hospital administration and healthcare management.
36. Project Management	Deep Neural Networks	Project Data	Accurate project success prediction, improved planning and monitoring	Demonstrates the effectiveness of deep learning models for project performance prediction.
37. Emerging Business Technologies	Artificial Intelligence, Blockchain, Edge Computing	Organizational and Operational Data	Business innovation, operational transformation	Reviews the impact of emerging technologies on modern business operations.
38. Project Management	Predictive Analytics, Artificial Intelligence, NLP	Project Data, Resource Data	Improved forecasting, risk management and resource allocation	Shows how AI enhances project planning and decision-making processes.
39. Database Management Systems	Artificial Intelligence, Optimization Algorithms	Database Performance Data	Improved system performance, anomaly detection	Demonstrates how AI improves database performance and operational efficiency.
40. Research Proposal Management Systems	Artificial Intelligence, Predictive Analytics	Proposal Evaluation Data	Process automation, improved evaluation efficiency	Shows how AI optimizes research proposal evaluation and management processes.

41. Working Capital Management	Machine Learning, Natural Language Processing	Financial Data, Operational Data	Optimized inventory and receivables, reduced financial risks, improved financial analysis	Demonstrates the potential of AI techniques to improve financial decision-making and working capital management.
42. Enterprise Incident Management	Natural Language Processing, Expert Systems, Multi-objective Optimization	Incident Data, Operational Data	Reduced response time, improved resource utilization, increased customer satisfaction	Presents an AI-powered incident management system for improving enterprise operational performance.
43. Oil and Gas Industry	Machine Learning, Deep Learning, Predictive Analytics	Operational Data, Sensor Data	Improved operational efficiency, predictive maintenance, enhanced safety	Explores the transformative role of AI in improving operational performance across oil and gas systems.
44. Systems Engineering Optimization	Optimization Algorithms, Swarm Intelligence, Machine Learning	System Performance Data, Simulation Data	Improved system efficiency and performance optimization	Reviews optimization techniques used in systems engineering to enhance complex system performance.
45. Real Estate Project Management	Machine Learning, Artificial Intelligence	Project Data, Market Data	Improved prediction accuracy, risk management, project sustainability	Demonstrates how AI improves planning and decision-making in real estate project management.

46. Data Management Systems	Artificial Intelligence, Machine Learning	Heterogeneous Data Sources	Optimized data pipelines, improved real-time decision-making	Shows how AI techniques enhance data pipeline management and reduce human errors.
47. Web Development Systems	Natural Language Processing, Machine Learning, Computer Vision	User Data, Web Interaction Data	Improved user experience, automated web processes	Demonstrates how AI improves web development through personalization and automation.
48. Enterprise Systems Integration	Hub Model, Service-Oriented Architecture	Organizational Data	Improved process integration, increased enterprise efficiency	Highlights the importance of system integration in enabling digital transformation.
49. Industrial Systems Engineering (RAMI 4.0)	Model-Based Systems Engineering, RAMI 4.0	Production System Data	Improved management of complex production systems	Presents an architecture supporting data-driven optimization in Industry 4.0 systems.
50. Artificial Intelligence as a Service (AIaaS)	Artificial Intelligence, Machine Learning	Cloud-based Pre-trained Models	Improved AI accessibility, scalable AI deployment	Discusses AIaaS as an approach for facilitating AI adoption in organizations.
51. Data-Centric Artificial Intelligence	Artificial Intelligence	Data-centric Development Data	Improved AI model performance through better data quality	Introduces the concept of data-centric AI and its implications for future AI development.

52. Structural Engineering Systems	Artificial Intelligence, Machine Learning	Structural Monitoring Data	Improved infrastructure resilience and design optimization	Demonstrates how AI improves structural design, monitoring, and infrastructure sustainability.
53. Renewable Energy Systems	Artificial Intelligence, ChatGPT	Energy System Data	Improved forecasting, optimization of renewable energy systems	Shows how generative AI can support renewable energy analysis and optimization.
54. Construction Industry	Generative AI, ChatGPT	Construction Design Data	Improved efficiency, task automation, better project decision-making	Explores how generative AI technologies can transform construction management processes.
55. Business Management Systems	ChatGPT, Large Language Models	Customer Data, Financial Data	Improved operational efficiency and decision-making	Demonstrates how generative AI can support business management and operational analysis.
56. Industry 4.0, Industry 5.0, Society 5.0	Generative AI, ChatGPT	Industrial and Social Data	Improved productivity, enhanced human-machine collaboration	Shows how generative AI technologies contribute to advanced industrial and societal systems.
57. Architectural Engineering	Generative AI, ChatGPT	Architectural Design Data	Improved design efficiency and sustainability	Demonstrates the role of generative AI in improving architectural design processes.

58. AEC Industry (Architecture, Engineering, Construction)	Artificial Intelligence, IoT, Big Data, Blockchain	Construction Data, Sensor Data	Improved resource management, enhanced project monitoring	Highlights the integration of multiple digital technologies for smart construction systems.
59. Smart Construction Management	Building Information Modeling, Artificial Intelligence	Project Data, BIM Data	Improved scheduling, cost control, quality and safety management	Demonstrates how integrating AI with BIM improves construction project management.
60. Smart Construction Monitoring Systems	Artificial Intelligence, Internet of Things	Sensor Data, Construction Data	Real-time monitoring, predictive maintenance, improved safety	Shows how AI and IoT technologies improve monitoring and efficiency in construction projects.
61. Business Operations	Artificial Intelligence	Business Data, Customer Data	Improved operational efficiency, personalized services, enhanced decision-making	Highlights how AI supports business operations through analytics, automation, and risk management.
62. Enterprise Resource Planning (ERP) Systems	Artificial Intelligence	Organizational Data, Financial Data	Improved organizational efficiency and strategic decision-making	Demonstrates how AI integration enhances ERP systems through automation and intelligent analytics.
63. IT Operations (AIOps)	Artificial Intelligence for IT Operations, Machine Learning	IT System Data, Log Data	Improved system monitoring, predictive maintenance, reduced downtime	Shows how AIOps improves IT service management through automated anomaly detection and root cause analysis.

64. Database Management and Big Data Analytics	Machine Learning, Artificial Intelligence	Database Data, Big Data	Improved query optimization, predictive analytics, enhanced data security	Demonstrates how AI improves performance and security in modern data management systems.
65. Project Management	Machine Learning, Artificial Intelligence	Project Data	Improved resource allocation, decision-making, and project outcomes	Shows how AI techniques support more effective project planning and management.
66. Supply Chain Management	Machine Learning, Robotics	Supply Chain Data, Demand Data	Improved operational efficiency, optimized logistics and resource utilization	Demonstrates the role of AI and robotics in developing more resilient and efficient supply chains.
67. Financial Risk Management	Big Data Analytics, Machine Learning, Predictive Modeling	Financial Data, Market Data	Improved fraud detection, risk prediction, regulatory compliance	Highlights how data analytics enhances financial risk assessment and strategic decision-making.
68. Project Management	Artificial Intelligence	Project Data	Improved planning, risk management, communication, and resource allocation	Demonstrates how AI applications enhance project efficiency and performance.
69. Predictive Financial Analysis	Random Forest, Advanced Data Engineering	Financial Data, Market Indicators	High prediction accuracy and improved financial forecasting	Shows how advanced data engineering techniques improve predictive analytics in financial systems.
70. Engineering Management	FEA, CFD, Machine Learning, Evolutionary Algorithms	Design Data, Performance Data	Improved structural performance, energy efficiency, and diagnostics	Demonstrates the use of advanced computational methods for optimizing mechanical engineering systems.
71. Lean Construction Management	Artificial Intelligence	Project Data, Resource Data	Improved efficiency, sustainability, and workflow optimization	Shows how AI supports lean construction principles and project performance improvement.

72. Industry 4.0 Smart Manufacturing	Artificial Intelligence, IoT, Cloud Computing	Operational Data, Sensor Data	Smart factories, predictive maintenance, automated production systems	Demonstrates how Industry 4.0 technologies enable intelligent and connected manufacturing systems.
73. Sustainable Energy Systems	Artificial Intelligence	Renewable Energy Data	Improved renewable energy optimization and grid efficiency	Highlights the role of AI in improving sustainability and efficiency in renewable energy systems.

The coding results presented in **Table 4.2** provide a structured classification of the selected studies based on several analytical dimensions, including application domains, techniques used, types of data, and the main outcomes reported in the literature. This structured coding enables a more systematic examination of the research trends related to the use of Artificial Intelligence and data analytics in Systems Engineering Management.

Based on this coded dataset, a **descriptive analysis** was conducted to identify the most prominent application areas, technological approaches, and research patterns within the reviewed studies. The following section presents the results of this descriptive analysis, beginning with the distribution of application domains identified in the selected articles.

4.4 Descriptive Analysis

To better understand the research trends in the reviewed literature, a descriptive analysis of the selected studies was conducted. The purpose of this analysis is to identify the primary application domains in which Artificial Intelligence and data analytics technologies are applied within Systems Engineering Management contexts.

Based on the coding results presented in Table 4.2, the selected studies were classified according to their **area of application**. This classification allows for the identification of the most frequently studied domains and highlights the diversity of industries and management areas in which AI-driven solutions are being implemented.

The distribution of application areas identified in the reviewed studies is presented in table 4.3

Table 4.1Application Areas

No	Category	Value	Percentage
1	Project Management	8	11.0%
2	Supply Chain Management	5	6.8%
3	Construction	4	5.5%
4	Civil Engineering	4	5.5%
5	Energy	3	4.1%
6	Oil and Gas Industry	3	4.1%
7	Risk Management	2	2.7%
8	Industry 4.0	2	2.7%
9	Data Management	2	2.7%
10	Systems Engineering	2	2.7%
11	Financial Predictive Analysis	2	2.7%
12	Mechanical Engineering	1	1.4%
13	Complex Industrial Systems	1	1.4%
14	Public Health	1	1.4%
15	Organizational Management	1	1.4%
16	Smart Grids	1	1.4%
17	Water Treatment and Desalination	1	1.4%
18	Robotic Process Automation	1	1.4%
19	Web Development	1	1.4%
20	Engineering Management	1	1.4%
21	Lean Construction	1	1.4%

The distribution of application domains identified in the reviewed studies is illustrated in **Figure 4.1**, which provides a visual representation of the categories presented in Table 4.3.

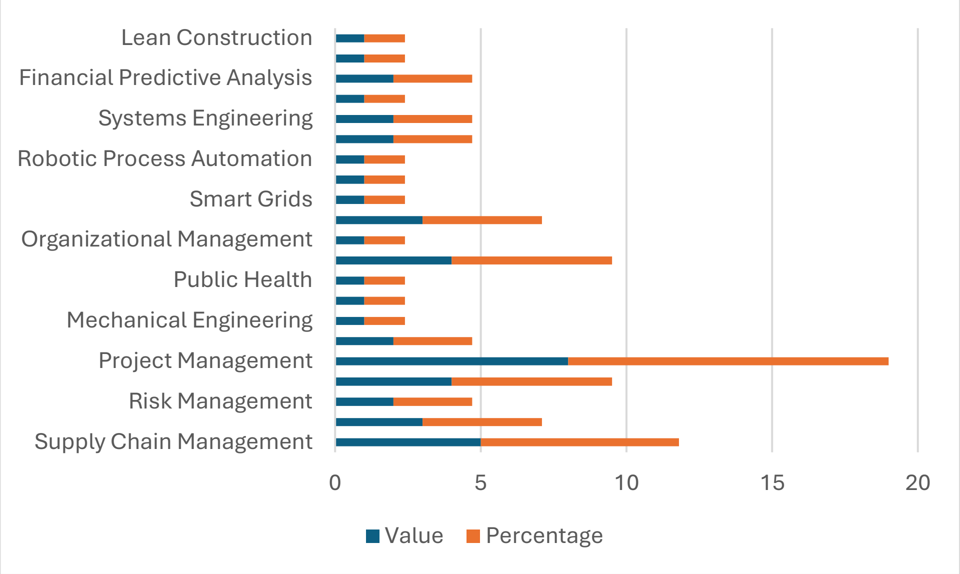

Figure 4.1 Distribution of Application Domains in selected studies

The results presented in Table 4.3 and Figure 4.1 show that Artificial Intelligence applications are distributed across a wide range of engineering and management domains. Among the identified categories, **project management represents the largest proportion of studies**, accounting for approximately **11%** of the reviewed literature. This indicates the growing interest in applying AI technologies to improve planning, scheduling, decision-making, and resource allocation in project-oriented environments.

Other prominent application areas include **supply chain management, construction, and civil engineering**, each representing a significant portion of the reviewed studies. These domains often involve complex operational systems and large volumes of data, making them suitable environments for the implementation of data-driven decision support systems.

Additionally, AI applications were identified in specialized domains such as **energy systems, oil and gas operations, smart grids, and water treatment systems**, demonstrating the broad applicability of AI technologies in different engineering sectors. Smaller numbers of studies were also found in areas such as **web**

development, robotic process automation, financial analytics, and lean construction, highlighting emerging research directions.

Overall, the distribution of application domains illustrates that Artificial Intelligence is increasingly being adopted across multiple industries to enhance operational efficiency, improve predictive capabilities, and support data-driven decision-making in complex engineering management environments.

The techniques used in the selected studies are summarized in **Table 4.4**, and their distribution is illustrated in **Figure 4.2**.

Table 4.4 Frequency of Techniques Used in Selected Articles

No	Category	Value	Percentage
1	Artificial Intelligence (AI)	40	54.8
2	Machine Learning (ML)	32	43.8
3	Deep Learning (DL)	6	8.2
4	Natural Language Processing (NLP)	6	8.2
5	Big Data Analytics (BDA)	5	6.8
6	Predictive Modeling	4	5.5
7	Evolutionary Algorithms	1	1.4

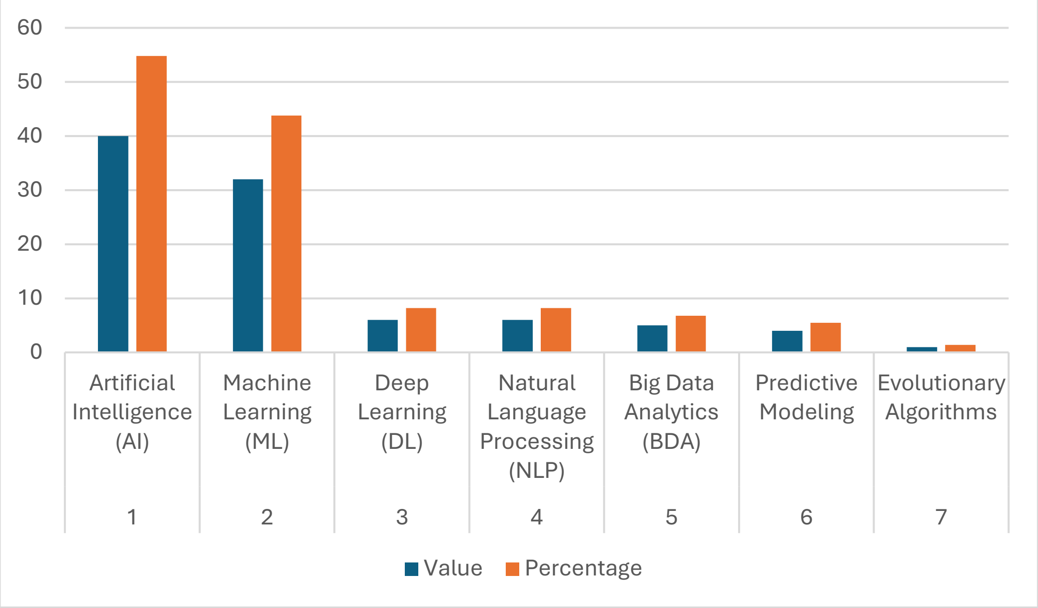

Figure 4.2 Distribution of Techniques Used in Selected Articles

The distribution of analytical techniques used in the selected studies is illustrated in Figure 4.2. The results show that Artificial Intelligence (AI) represents the most frequently applied approach, accounting for approximately 43% of the reviewed studies. Machine Learning (ML) also appears prominently, representing about 34% of the analyzed literature.

Other techniques such as Deep Learning (DL), Natural Language Processing (NLP), and Big Data Analytics (BDA) appear with lower frequencies, indicating their more specialized application in specific engineering and management contexts. Predictive modeling techniques are also present in several studies, particularly in applications involving forecasting, risk analysis, and decision support.

Overall, the distribution indicates that while Artificial Intelligence and Machine Learning dominate the research landscape, other advanced analytical techniques are increasingly being integrated to support complex decision-making processes in Systems Engineering Management.

To further analyze the characteristics of the reviewed studies, the types of data used in the selected articles were categorized. Table 4.5 presents the distribution of studies according to the primary data types employed in their analytical approaches.

Table 4.5Data Types Used in Selected Articles

No	**Category**	**Percent**
1	Operational Data	34.2
2	Project Data	21.9
3	Financial Data	9.6
4	Sensor Data	11.0
5	Supply Chain Data	6.8
6	Market Data	2.7
7	Text Data	4.1

The distribution of data types used in the selected studies is illustrated in Figure 4.3.

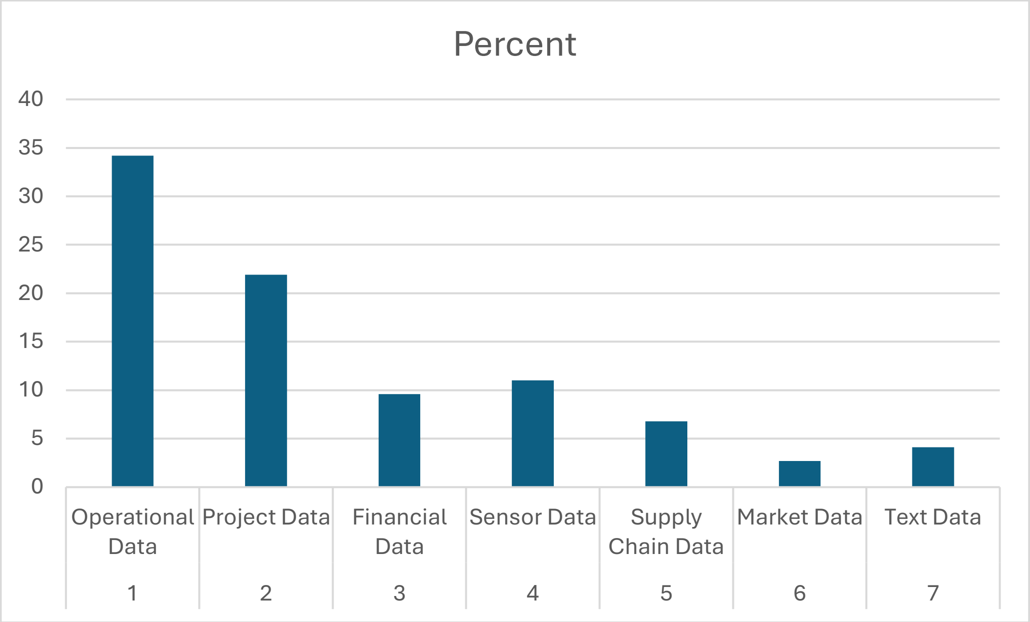

Figure 4.3 Distribution of Data Types Used in Selected Articles

As shown in Table 4.5 and Figure 4.3, operational data represents the most frequently used data type in the reviewed studies, accounting for approximately 34.2% of the analyzed literature. This reflects the strong focus on real-world operational processes in systems engineering management, where large volumes of performance and process data are generated.

Project data also represents a significant portion of the analyzed studies (21.9%), highlighting the importance of project-based information in areas such as scheduling, resource allocation, and project risk analysis. Sensor data and financial data appear in several studies as well, particularly in applications related to monitoring systems, predictive maintenance, and financial decision-making.

Other data sources such as supply chain data, text data, and market data appear less frequently but still play important roles in specific analytical contexts. These findings indicate that artificial intelligence and data analytics applications in systems engineering management rely heavily on operational and project-related data to support predictive modelling, decision-making, and process optimization.

4.5 Inferential and Statistical Analyses

While the previous section focused on descriptive statistics of the reviewed studies, this section presents inferential and statistical analyses aimed at identifying relationships between key variables extracted from the literature. Cross-tabulation analysis was employed to explore the interactions between variables such as application area, data type, analytical techniques, and the key outcomes reported in the selected studies. These analyses provide deeper insights into how Artificial Intelligence methods are applied across different domains of Systems Engineering Management.

4.5.1 Relationship between Application Area and Technique Used

To understand how different Artificial Intelligence techniques are utilized across various domains, a cross-tabulation analysis was conducted between the application area and the analytical technique used in the reviewed studies.

Table 4.6 Relationship between "Application Area" and "Technique Used"

Application Area	ML	DL	RL	Fuzzy	NLP	Big Data	Data Sci	MCDM	Other
Supply Chain Management	8	2	1	0	1	5	3	0	0
Energy	5	4	2	1	0	2	1	3	0
Risk Management / Construction	4	1	0	0	0	1	2	1	0
Construction	5	1	0	0	1	2	1	0	1
Project Management	1	0	0	0	4	0	0	0	1
Other	7	3	1	0	2	3	2	2	1

To provide a clearer visual representation of these relationships, the distribution is illustrated in Figure 4.4.

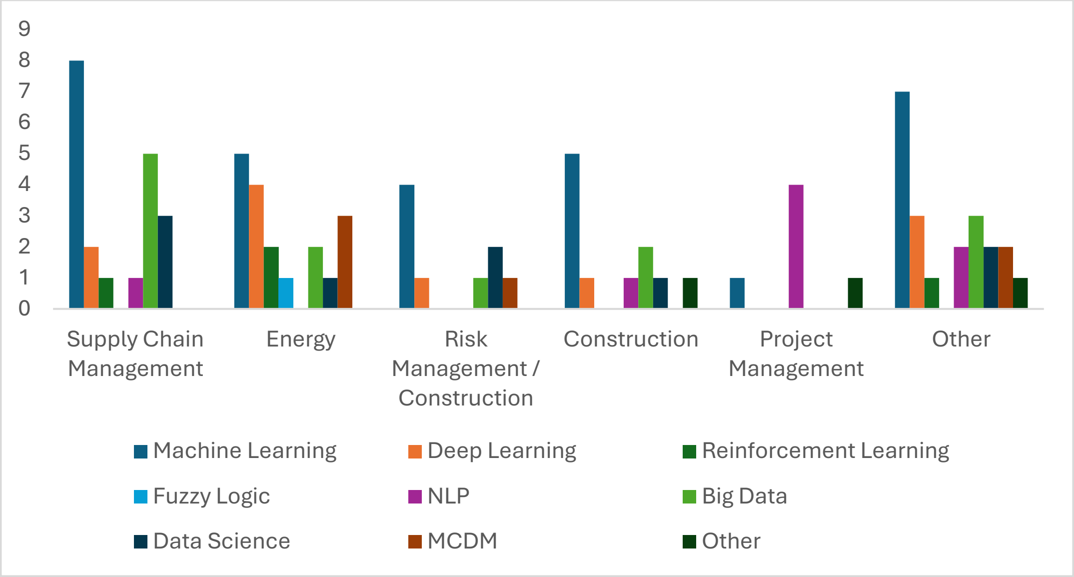

Figure 4.4 Relationship between Application Area and Technique Used in Selected Articles

The results indicate that **Machine Learning** is the most frequently applied technique across several application domains, particularly in **supply chain management, energy systems, and construction-related studies**. This reflects the suitability of machine learning algorithms for predictive analysis, optimization, and decision-support tasks in complex engineering environments.

Deep learning and reinforcement learning techniques appear in fewer studies and are typically applied in more specialized contexts. Natural language processing is mainly observed in **project management applications**, where textual data and communication processes are analyzed. Overall, the analysis suggests that the selection of analytical techniques depends strongly on the characteristics of the application domain and the nature of the available data.

4.5.2 Relationship between Data Type and Technique Used

Another important aspect of the analysis involves examining how the **type of data used** influences the selection of analytical techniques.

Table 4.7 summarizes the relationship between data types and the Artificial Intelligence techniques applied in the reviewed studies.

Table 4.7 Relationship between "Data Type" and "Technique Used"

Data Type	ML	DL	RL	Fuzzy	NLP	Big Data	Data Sci	Other
Operational Data	17	7	2	1	5	7	5	3
Historical Data	9	2	0	0	2	3	4	0
Sensor Data	5	4	1	0	0	1	0	1
Text Data	0	1	0	0	4	0	0	0
Diverse Data	2	1	0	0	0	1	1	0
Other	2	0	0	0	0	0	0	0

The graphical representation of this relationship is shown in **Figure 4.5**.

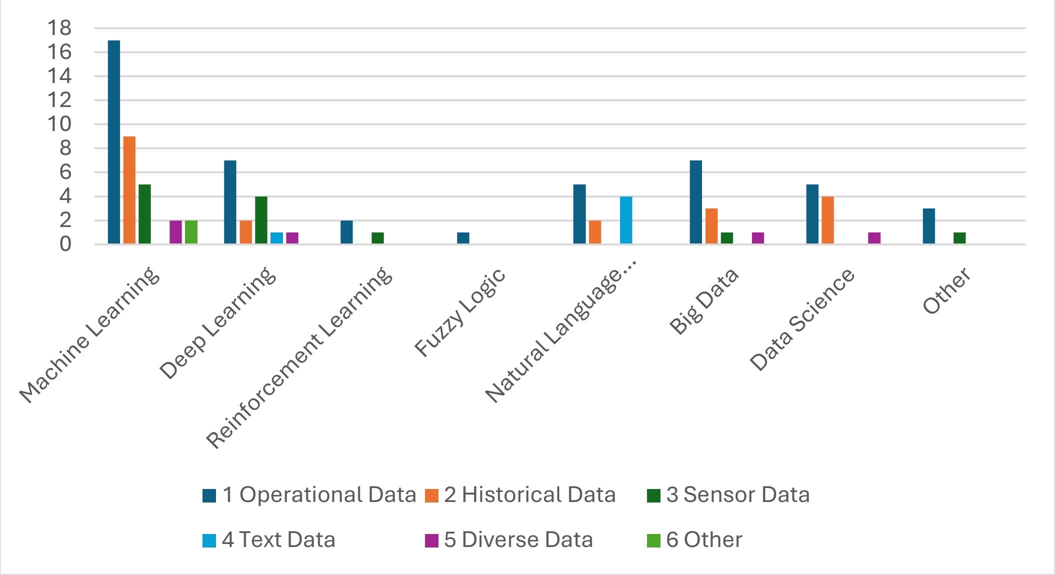

Figure 4.5 Relationship between "Data Type" and "Technique Used" in Selected Articles

The findings reveal that **operational data and historical data** are the most commonly used data types in studies applying machine learning techniques. These data sources are frequently used for predictive modelling and operational optimization.

Sensor data is often associated with monitoring systems and real-time data analysis, while textual data is primarily analyzed using natural language processing methods. The results demonstrate that the type of available data significantly influences the choice of analytical techniques in Artificial Intelligence applications

4.5.3 Relationship between Application Area and Key Results

This analysis explores the relationship between the **application domains** of the reviewed studies and the **key outcomes achieved through the application of Artificial Intelligence techniques**.

Table 4.8 presents the distribution of key outcomes across different application areas.

Table 4.8 Relationship between "Application Area" and "Key Results"

Application Area	Cost Reduction	Efficiency Improvement	Forecasting	Risk Reduction	Safety	Sustainability	Other
Supply Chain Management	6	5	5	1	0	2	2
Energy	1	4	4	0	2	4	1
Risk Management, Construction	3	2	2	4	2	0	1
Construction	3	4	3	2	1	0	2
Project Management	0	2	0	1	2	0	3
Other	3	3	3	2	1	2	4

The visual representation of these relationships is provided in **Figure 4.6**.

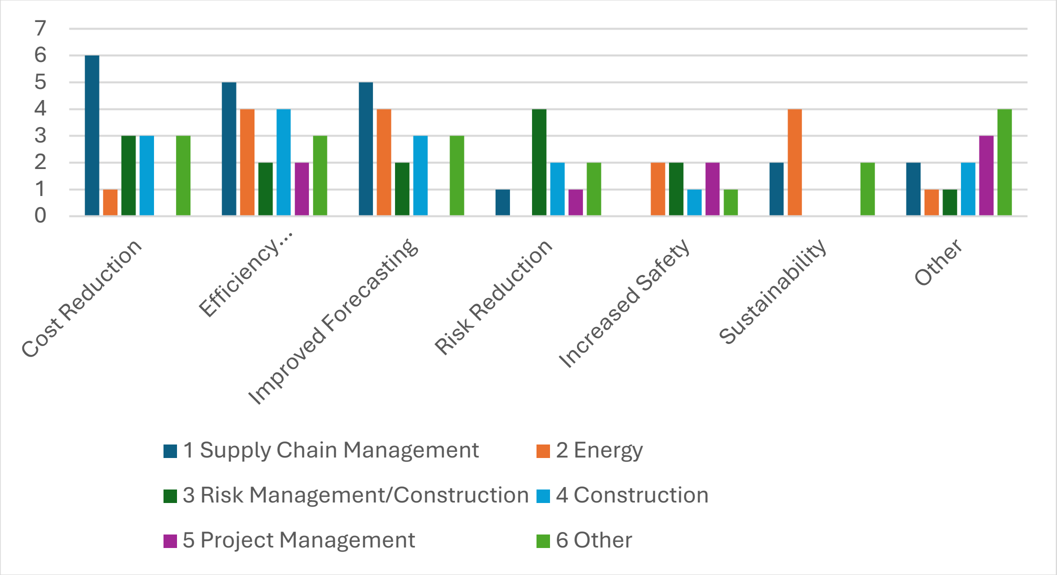

Figure 4.6 Relationship between "Application Area" and "Key Results" in Selected Articles

The results indicate that **efficiency improvement and cost reduction** are among the most frequently reported benefits of Artificial Intelligence applications. These outcomes are particularly prominent in supply chain management, construction, and energy-related studies.

Risk reduction and improved safety also appear as important outcomes in several application domains, especially in engineering and construction contexts where predictive analytics can prevent operational failures. Additionally, sustainability improvements are reported in a number of studies, reflecting the growing use of AI technologies to support environmentally sustainable engineering practices.

4.5.4 Relationship between Technique Used and Key Results

This analysis investigates how different analytical techniques contribute to specific outcomes reported in the reviewed studies.

Table 4.9 presents the cross-tabulation between the **analytical techniques used** and the **key results achieved**.

Table 4.9 Relationship between "Technique Used" and "Main Results"

Technique Used	Cost Reduction	Efficiency Improvement	Forecasting	Risk Reduction	Safety	Sustainability	Other
Machine Learning	11	11	9	3	5	5	5
Deep Learning	1	3	4	0	2	3	1
Reinforcement Learning	0	2	1	0	0	0	0
Other	4	7	7	3	4	3	7

The relationship between analytical techniques and their outcomes is illustrated in **Figure 4.7**.

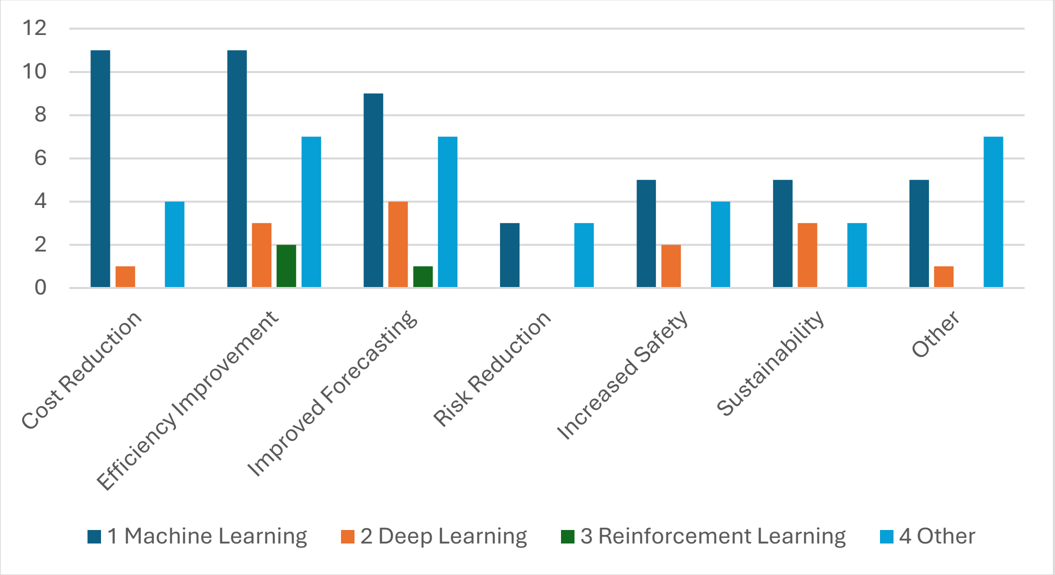

Figure 4.1Relationship between "Technique Used" and "Key Results" in Selected Articles

The results show that **machine learning techniques are strongly associated with improvements in operational efficiency, cost reduction, and predictive capabilities**. These techniques are widely used in forecasting, optimization, and decision-support applications.

Deep learning methods also contribute to improved predictive performance, particularly in cases involving complex datasets. Other analytical techniques appear less frequently but still provide valuable support in specialized decision-making and optimization tasks.

4.5.5 ChatGPT Usage Levels Across Different Fields

In addition to traditional Artificial Intelligence techniques, this review also examined the emerging application of **generative AI tools such as ChatGPT** in different domains.

Table 4.10 summarizes the distribution of ChatGPT usage across different application areas identified in the reviewed studies.

Table 4.10 ChatGPT Usage Levels Across Different Fields

Application Area	Yes	No
Project Management	4	0
Urban Architecture	2	0
Business Management	2	0
Industry 4.0	1	0
Sustainable Energy	1	0
Construction	2	0
Other	0	1

The graphical representation of these results is shown in **Figure 4.8**.

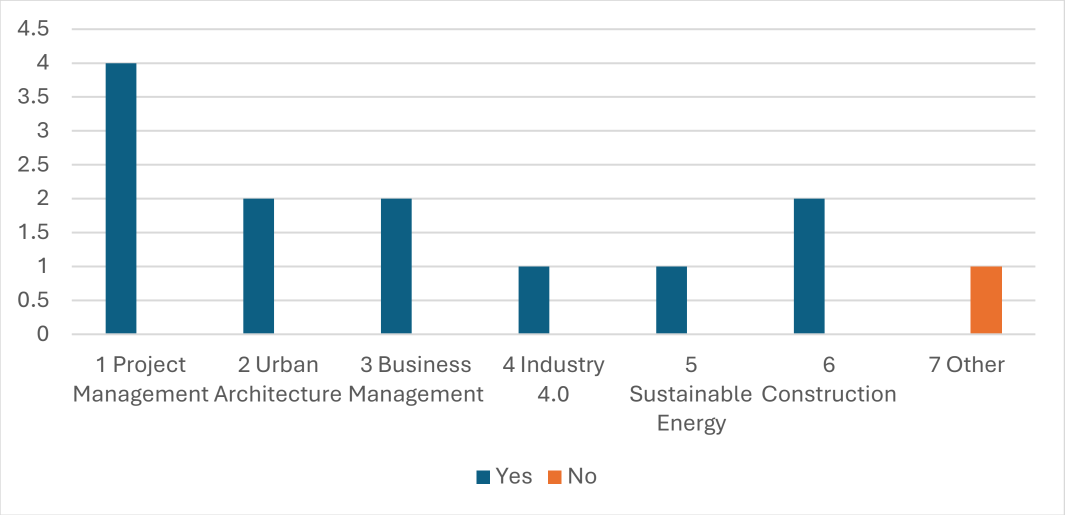

Figure 4.8 ChatGPT Usage Levels across different fields

The results indicate that ChatGPT applications are most commonly observed in **project management, urban architecture, and business management contexts**, where natural language processing capabilities can support documentation, communication, and decision-support tasks.

Although the number of studies using ChatGPT remains relatively limited, the findings suggest that generative AI technologies are gradually emerging as valuable tools in systems engineering management and related fields.

4.5.6 Chi-Square statistical Analysis

To statistically examine the relationships identified in the cross-tabulation analyses, a **Chi-Square Test of Independence** was conducted. The Chi-Square test is a widely used statistical method for determining whether a significant association exists between two categorical variables. In the context of this study, the test was applied to evaluate whether relationships exist between the main dimensions identified in the systematic literature review, namely **application areas, data types, analytical techniques, and the primary outcomes reported in the selected studies**.

The analysis was based on contingency tables constructed from the coded dataset of the **73 studies included in the systematic literature review**. Each study was categorized according to its application domain, the analytical technique employed, the type of data used, and the main outcomes reported. Frequency counts derived from these categories were used to generate cross-tabulations, which formed the basis for the Chi-Square calculations.

The Chi-Square test evaluates the null hypothesis that **no association exists between the variables being examined**. Accordingly, the hypotheses tested in this analysis are defined as follows:

H_0 (Null Hypothesis): There is no statistically significant association between the variables under investigation.

H_1 (Alternative Hypothesis): A statistically significant association exists between the variables under investigation.

A **significance level of $\alpha = 0.05$** was adopted for the statistical tests. If the calculated p-value is less than the significance level, the null hypothesis is rejected, indicating the presence of a statistically significant relationship between the variables.

Table 4.11 presents the results of the Chi-Square tests conducted for the main relationships examined in this study.

Table 4.2 Chi-Square Test Results for Variable Relationships

Relationship Investigated	**Chi-Square**	**Degrees of Freedom**	**p-value**	**Interpretation**
Application Area & Technique Used	50.39	40	0.126	No significant association
Data Type & Technique Used	39.50	35	0.276	No significant association
Application Area & Main Results	33.09	30	0.319	No significant association
Technique Used & Main Results	12.65	18	0.812	No significant association

As shown in Table 4.11, all calculated p-values are greater than the significance threshold of **0.05**. Therefore, the null hypothesis cannot be rejected for any of the examined relationships. This indicates that the statistical analysis does not pro

vide sufficient evidence to conclude that significant associations exist between application areas, data types, analytical techniques, and the outcomes reported in the reviewed studies.

The absence of statistically significant relationships suggests that the use of artificial intelligence techniques in systems engineering management research is **not strongly restricted to specific domains, data types, or outcome categories**. Instead, many analytical techniques appear to be applied across multiple application areas and research contexts.

This finding reflects the **flexibility and general applicability of artificial intelligence methods**, particularly machine learning and data analytics approaches, which can be adapted to a wide variety of engineering management problems. As a result, similar analytical techniques are often employed across different domains, reducing the likelihood of strong statistical associations between specific categories in the literature.

It should also be noted that the dataset used for the analysis consists of a **moderate number of studies collected through a systematic literature review**, which may result in relatively small frequency counts within certain contingency table cells. Consequently, the results of the Chi-Square analysis should be interpreted with caution, as small cell frequencies may limit the statistical power of the test.

Despite the lack of statistically significant relationships, the **descriptive and cross-tabulation analyses presented in previous sections still provide valuable insights** into research trends within the field. In particular, the analysis highlights the widespread use of machine learning techniques across multiple application domains, indicating the growing importance of data-driven approaches in supporting systems engineering management processes.

4.6 Content Analysis

Content analysis was conducted to identify recurring themes, patterns, and key concepts within the descriptions of the selected articles. By systematically reviewing the summaries and main findings of the studies, it was possible to extract the most frequently occurring keywords and thematic categories. This qualitative analysis helps reveal the dominant research directions and conceptual focus areas within the literature related to Artificial Intelligence applications in Systems Engineering Management.

4.6.1 Frequent Keywords

The analysis of article descriptions revealed several keywords that appear repeatedly across the reviewed studies. These keywords reflect the primary concepts and research focus areas within the literature. The most frequently observed keywords include:

- Artificial Intelligence (AI)
- Machine Learning (ML)
- Data
- Improvement
- Efficiency
- Management
- Optimization
- Prediction
- Supply Chain
- Energy

These keywords highlight the strong emphasis on data-driven technologies and performance improvement within engineering management environments.

4.6.2 Main Themes Identified in the Literature

Based on the content analysis of the article descriptions, several major themes were identified. These themes represent the dominant research topics addressed in the reviewed studies.

Application of Artificial Intelligence in Various Industries

A large portion of the reviewed articles focuses on the implementation of Artificial Intelligence technologies across different industries. These include supply chain management, energy systems, construction, project management, manufacturing, and other engineering-related sectors. The studies demonstrate how AI technologies can enhance operational processes and improve system performance in complex industrial environments.

Improving Efficiency and Reducing Costs

Improving operational efficiency and reducing organizational costs are among the most frequently reported objectives in the reviewed literature. Many studies emphasize the role of AI techniques in optimizing processes, minimizing waste, and improving productivity across various engineering management applications.

Data Analysis and Predictive Capabilities

Another dominant theme is the use of Artificial Intelligence for advanced data analysis and predictive modeling. AI methods such as machine learning are widely applied to analyze large datasets and forecast future trends, enabling organizations to anticipate potential risks and make more informed decisions.

Process Automation

Several studies highlight the use of AI technologies to automate operational processes. Automation through AI systems helps reduce human intervention, increase operational speed, and improve the accuracy of repetitive tasks within engineering and management environments.

Intelligent Decision-Making

Artificial Intelligence is frequently applied to support decision-making processes in organizations. AI-driven decision-support systems assist managers in analyzing complex information, evaluating alternatives, and making more effective strategic decisions.

Sustainability and Sustainable Development

Although less frequently discussed than other themes, some studies address the role of AI technologies in promoting sustainability and environmentally responsible practices. These studies examine how AI can support energy optimization, resource efficiency, and sustainable system design.

4.7 Trend Analysis

The purpose of this analysis is to examine the temporal distribution of the selected studies and identify trends in the development of research related to Artificial Intelligence and data analytics in Systems Engineering Management. By analyzing the publication years of the selected articles, it is possible to observe how research activity in this field has evolved over time.

Table 4.12 presents the distribution of the reviewed articles according to their year of publication. This distribution helps illustrate the growth of academic interest in the application of Artificial Intelligence and data-driven technologies in engineering and management systems.

Table 4.12 Distribution of Selected Articles by Publication Year

No	Year of Publication	Number of Articles
1	2025	2
2	2024	17
3	2023	16
4	2022	3
5	2021	6
6	2020	2
7	2018	1
8	2014	1

As shown in Table 4.12, the majority of the selected studies were published in recent years. The highest number of publications occurred in 2024 (17 articles) and 2023 (16 articles), indicating a significant increase in research activity during this period. This trend reflects the growing importance of Artificial Intelligence technologies in engineering management and industrial systems.

Earlier years show a relatively smaller number of publications, with only a few studies identified between 2014 and 2020. This suggests that the integration of AI and data analytics into engineering management has become more prominent in recent years as technological capabilities and data availability have expand.

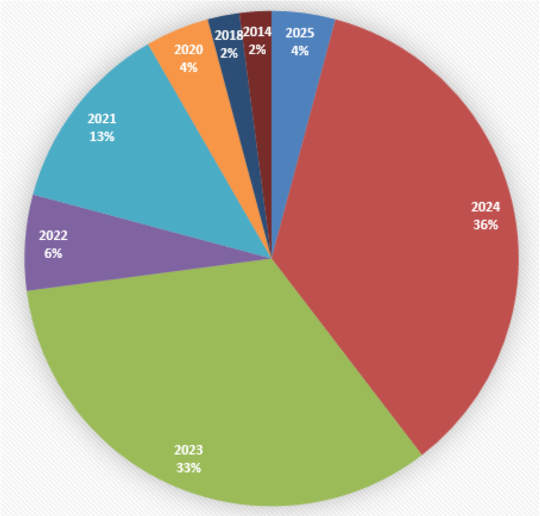

Figure 4.9 Distribution of Selected Articles by Publication Year

The trend illustrated in Figure 4.9 clearly demonstrates the rapid growth of research interest in Artificial Intelligence applications in engineering systems over the past few years. The concentration of studies in recent years indicates that this field is still evolving and expanding, with increasing attention from both researchers and industry practitioners. Despite this growth, the relatively limited number of earlier studies suggests that further research opportunities remain in exploring advanced AI techniques and their applications in engineering management.

4.8 Weighting Analysis

The purpose of this weighting analysis is to determine the relative importance of different application domains, analytical techniques, and data types identified in the reviewed articles. After completing the coding and classification of the selected studies, the next step is to assign weights to the identified elements in order to evaluate their relative significance within the research field.

In this study, weighting is performed based on three criteria derived from the literature review and expert opinion:

- **Frequency Weight (40%)** – representing how often each element appears in the reviewed articles.
- **Keyword Weight (30%)** – reflecting the importance of keywords associated

with each element in the literature.

• **Impact Weight (30%)** – representing the perceived importance of each element based on the evaluation of domain, technique, and data impact.

These three components are combined to calculate the **final weight** of each element.

4.8.1 Frequency-Based Weighting

The first stage of the weighting process is based on the frequency of occurrence of each element in the reviewed articles. In this step, the key characteristics of each article—including application area, analytical technique, data type, and impact indicators—were extracted and organized. Table 4.13 presents the primary variables used in the first stage of the weighting analysis.

Table 4.13 Important Variables Classified by Articles in the First Weighting Stage

article No	Application Area	Technique Used	Data Type	Impact of the field	Impact of the technique	Impact of the data
1	Supply Chain Management, MES	Machine Learning	Operational Data, Historical Data, Sensor Data	4	5	4
2	Energy	Machine Learning, Deep Learning, Reinforcement Learning, Fuzzy Logic	Sensor Data, Operational Data	5	4	4
3	Risk Management, Construction	Machine Learning, Predictive Analytics	Historical Data, Operational Data	4	4	3
4	Construction	Data Analytics, Predictive Analytics, Machine Learning	Historical Data, Operational Data	4	4	3
5	Supply Chain Management	Machine Learning, Big Data Analytics	Historical Data, Operational Data	4	4	3
6	Project Management	Natural Language Processing (NLP)	Text Data	4	4	4
7	Construction, Project Management	Big Data, Data Science, Machine Learning	Diverse Data	4	4	3
8	Energy, Sustainable Development	Machine Learning, MCDM, Fuzzy AHP, TOPSIS	Operational Data	5	4	4
9	Oil and Gas Industry	Machine Learning, Data Science	Sensor Data, Historical Data	4	4	4
10	Smart Grids	Big Data Analytics, Machine Learning, Artificial Intelligence	AMI Data, PMU Data	5	4	4
11	Mechanical Engineering	Deep Learning, Machine Learning	Design Data, Performance Data	4	4	3
12	Complex Industrial Systems	Deep Learning, Reinforcement Learning	Operational Data, Simulation Data	4	4	4
13	Pandemic Management, Public Health	Artificial Intelligence, Machine Learning	Medical Data, Epidemiological Data	5	4	4
14	Civil Engineering	Multi-Criteria Decision Making, Structural Modeling	Project Data, Expert Survey Data	4	3	3

15	Urban Architecture	Machine Learning	Design Data, Construction Data	4	4	3
16	Organizational Management	Machine Learning	Organizational Data	4	4	3
17	Oil and Gas Industry	Machine Learning, Data Science	Sensor Data, Historical Data	4	4	4
18	Plant Molecular Pharmacology	Machine Learning, Deep Learning	Biological Data, Structural Data	4	4	4
19	Software Engineering	Machine Learning	Code Data, Test Data	4	4	3
20	Industrial Engineering	Machine Learning	Process Data, Supply Chain Data	4	4	3
21	Business Management	Data Analytics	Customer Data, Supply Chain Data	4	4	3
22	IT Infrastructure Management	AI-Based Active Analytics	System Performance Data, Log Data	4	4	4
23	Fault Diagnosis in Data Engineering Systems	Machine Learning	System Data, Log Data	4	4	4
24	Supply Chain Management	Artificial Intelligence, Internet of Things (IoT)	Supply Chain Data, Sensor Data	4	4	4
25	Wireless Networks	Big Data Analytics, Machine Learning	Network Data, Performance Data	4	4	4
26	Water Purification	Artificial Intelligence	Pollutant Absorption Data	4	4	4
27	Robotic Process Automation	Neural Networks, Natural Language Processing	Process Data	4	4	3
28	Supply Chain Optimization	Machine Learning	Secondary Supply Chain Data	4	4	3
29	Supply Chain Management	Artificial Intelligence	Demand Data, Inventory Data	4	4	3
30	Sustainable Agriculture	Artificial Intelligence	Product Data, Climate Data	4	4	4
31	Management Information Systems	Artificial Intelligence	Historical Data, Organizational Data	4	4	3
32	Technology Management	Bibliometric Analysis	Educational Big Data	3	2	2
33	Process Systems Engineering	Generative AI Models	Energy Production Data	4	4	3
34	Renewable Energy Systems	Machine Learning	Administrative Data, Clinical Data	4	4	4
35	Hospital Management	Artificial Intelligence	Data Type	4	4	4
36	Project Management	Deep Neural Networks	Project Data	4	5	3
37	Emerging Business Technologies	Artificial Intelligence	Organizational Data	4	4	3
38	Project Management	Predictive Analytics, Artificial Intelligence	Project Data	4	4	3
39	Database Management Systems	Artificial Intelligence	Database Data	4	4	4
40	Research Recommender Systems	Artificial Intelligence	Document Validation Data	4	4	3

41	Working Capital Management	Machine Learning	Financial Data	4	4	3
42	Organizational Incident Management	Natural Language Processing	Incident Data	4	4	4
43	Oil and Gas Industry	Machine Learning	Operational Data	4	4	4
44	Systems Engineering	Optimization, Machine Learning	System Performance Data	4	4	3
45	Structural Engineering	Artificial Intelligence	Structural Health Monitoring Data	4	4	3
46	Renewable Energies	ChatGPT	Energy Data	4	4	3
47	Construction	ChatGPT	Design Data	4	4	3
48	Business Management	ChatGPT	Customer Data	4	4	3
49	Industry 4.0	ChatGPT	Production Data	4	4	3
50	Artificial Intelligence as a Service	Artificial Intelligence	Pre-trained Models	3	4	2
51	Data-Centric Artificial Intelligence	Artificial Intelligence	Systematic Data	3	4	3
52	Structural Engineering	Artificial Intelligence	Structural Health Monitoring Data	4	4	3
53	Renewable Energies	ChatGPT	Energy Production Data	4	4	3
54	Construction	ChatGPT	Design Data	4	4	3
55	Business Management	ChatGPT	Customer Data	4	4	3
56	Industry 4.0	ChatGPT	Production Data	4	4	3
57	Architectural Engineering	ChatGPT	Design Data	4	4	3
58	AEC Industry	Artificial Intelligence, IoT	Building Data	4	4	4
59	Smart Construction Management	BIM, Artificial Intelligence	Project Data	4	4	3
60	AEC Industry	Artificial Intelligence, IoT	Sensor Data	4	4	4
61	Business Operations	Artificial Intelligence	Commercial Data	4	4	3
62	ERP Systems	Artificial Intelligence	Organizational Data	4	4	3
63	IT Operations	AIOps	IT Data	4	4	4
64	Data Management	Artificial Intelligence	Database Data	4	4	4
65	Project Management	Machine Learning	Project Data	4	4	3
66	Supply Chain Management	Machine Learning, Robotics	Supply Chain Data	4	4	3
67	Financial Risk Management	Big Data Analytics	Financial Data	4	4	3
68	Project Management	Artificial Intelligence	Project Data	4	4	3
69	Financial Predictive Analytics	Random Forest	Financial Data	4	5	3
70	Mechanical Engineering	FEA, CFD, Machine Learning	Performance Data	4	4	3

71	Lean Construction	Artificial Intelligence	Project Data	4	4	3
72	Industry 4.0	AI, IoT	Operational Data	4	4	4
73	Sustainable Energy	Artificial Intelligence	Renewable Resources Data	4	4	4

The information presented in Table 4.13 forms the basis for calculating the relative importance of the identified elements. Each article contributes to the overall weighting through its application area, analytical technique, and type of data used. The impact indicators assigned to each dimension reflect the perceived importance of the field, technique, and data type in the context of Artificial Intelligence applications in engineering management.

4.8.2 Weighting of Application Domains

Using the extracted variables, the relative weights of the application domains were calculated. The weighting considers the frequency of occurrence, keyword importance, and the average impact score assigned to each domain. The results of this calculation are presented in Table 4.14.

Table 4.14 Weighting of selected articles by field

Element	**Number of repetitions (frequency)**	**Frequency (40%) weight**	**Keyword (30%) weight**	**Average impact**	**Impact weight (30%)**	**Final weight**
Supply Chain Management	4	1.60%	6.00%	4.00	12.00%	23.60%
Energy	3	1.20%	6.00%	4.33	13.00%	20.53%
Construction	4	1.60%	6.00%	4.00	12.00%	23.60%
Project Management	4	1.60%	6.00%	4.00	12.00%	23.60%
Oil and Gas Industry	2	0.80%	6.00%	4.00	12.00%	18.80%
Mechanical Engineering	1	0.40%	6.00%	4.00	12.00%	18.40%
Complex Industrial Systems	1	0.40%	6.00%	4.00	12.00%	18.40%
Pandemic Management	1	0.40%	6.00%	5.00	15.00%	21.40%
Civil Engineering	2	0.80%	6.00%	3.50	10.50%	17.30%
Urban Architecture	1	0.40%	6.00%	4.00	12.00%	18.40%
Organizational Management	1	0.40%	6.00%	4.00	12.00%	18.40%
Plant Molecular Pharmacology	1	0.40%	6.00%	4.00	12.00%	18.40%

Software Engineering	1	0.40%	6.00%	4.00	12.00%	18.40%
Industrial Engineering	1	0.40%	6.00%	4.00	12.00%	18.40%
Business Management	1	0.40%	6.00%	4.00	12.00%	18.40%
IT Infrastructure Management	1	0.40%	6.00%	4.00	12.00%	18.40%
Systems Engineering	1	0.40%	6.00%	4.00	12.00%	18.40%
Renewable Energy	2	0.80%	6.00%	4.00	12.00%	18.80%

The results indicate that **Supply Chain Management, Construction, and Project Management** receive the highest final weights among the application domains. This confirms the earlier descriptive analysis, which showed that these areas are the most frequently studied contexts for the application of Artificial Intelligence techniques.

Other domains such as **Energy, Oil and Gas Industry, and Civil Engineering** also demonstrate notable importance, reflecting the growing adoption of AI technologies in complex engineering environments.

4.8.3 Weighting of Techniques

In the next stage, the weighting analysis focuses on the analytical techniques used in the reviewed studies. The techniques were evaluated based on their frequency of use, keyword relevance, and average impact score. The results of this analysis are summarized in Table 4.15.

Table 4.15 Weighting of selected articles based on techniques

Element	**Number of repetitions (frequency)**	**Frequency (40%) weight**	**Keyword weight (30%)**	**Average impact**	**Impact weight (30%)**	**Final weight**
Machine Learning	23	9.20%	6.90%	4.18	12.54%	28.64%
Deep Learning	5	2.00%	1.50%	3.60	10.80%	14.30%
Reinforcement Learning	2	0.80%	0.60%	3.50	10.50%	11.90%
Fuzzy Logic	1	0.40%	0.30%	3.00	9.00%	9.70%
Data Analytics	4	1.60%	1.20%	3.75	11.25%	14.05%
Natural Language Processing (NLP)	5	2.00%	1.50%	4.00	12.00%	15.50%
MCDM, Fuzzy AHP, TOPSIS	1	0.40%	0.30%	3.00	9.00%	9.70%
Data Science	3	1.20%	0.90%	4.00	12.00%	14.10%

MBSE ،RAMI 4.0	1	0.40%	0.30%	4.00	12.00%	12.70%
Random Forest	1	0.40%	0.30%	4.33	13.00%	13.70%
CFD ،FEA	1	0.40%	0.30%	4.00	12.00%	12.70%

The results show that **Machine Learning** receives the highest final weight among the analyzed techniques. This finding highlights the central role of machine learning algorithms in Artificial Intelligence applications across engineering management domains.

Other techniques such as **Deep Learning, Natural Language Processing, and Data Analytics** also show significant contributions, while more specialized methods such as **Fuzzy Logic and Multi-Criteria Decision-Making (MCDM)** appear less frequently in the reviewed literature.

4.8.4 Weighting of Data Types

The final stage of the weighting analysis examines the types of data used in the reviewed studies. Different data categories were evaluated based on their frequency of occurrence and impact on analytical outcomes. The calculated weights for each data type are presented in Table 4.16.

Table 4.16 Weighting of selected articles based on data type

Element	Number of repetitions (frequency)	Frequency (40%) weight	Keyword (30%) weight	Average impact	Impact weight (30%)	Final weight
Operational data	11	4.40%	3.30%	4.25	12.75%	20.45%
Historical data	8	3.20%	2.40%	3.25	9.75%	15.35%
Sensor data	9	3.60%	2.70%	4.00	12.00%	18.30%
Textual data	2	0.80%	0.60%	3.00	9.00%	13.40%
Design data	4	1.60%	1.20%	3.25	9.75%	14.55%
Performance data	2	0.80%	0.60%	3.00	9.00%	13.40%
Medical data	1	0.40%	0.30%	3.50	10.50%	14.20%
Biological data	1	0.40%	0.30%	3.00	9.00%	12.70%
Protein structural data	1	0.40%	0.30%	3.25	9.75%	13.45%
Code data	2	0.80%	0.60%	3.75	11.25%	14.65%
Test data	2	0.80%	0.60%	3.75	11.25%	14.65%
Requirements data	1	0.40%	0.30%	3.00	9.00%	12.70%

Process data	4	1.60%	1.20%	4.00	12.00%	14.80%
Supply chain data	4	1.60%	1.20%	4.00	12.00%	14.80%
Customer data	1	0.40%	0.30%	4.25	12.75%	16.45%
Market data	1	0.40%	0.30%	4.00	12.00%	16.70%
System performance data	4	1.60%	1.20%	4.00	12.00%	14.80%
Log data	1	0.40%	0.30%	3.25	9.75%	13.45%
Network data	4	1.60%	1.20%	4.00	12.00%	14.80%
AMI data, PMU data	1	0.40%	0.30%	3.75	11.25%	14.95%
Contaminant absorption data	1	0.40%	0.30%	3.50	10.50%	14.20%
Process data	4	1.60%	1.20%	4.00	12.00%	14.80%
Secondary supply chain data	1	0.40%	0.30%	3.00	9.00%	12.70%
Product data	4	1.60%	1.20%	4.00	12.00%	14.80%
Climate data	4	1.60%	1.20%	4.00	12.00%	14.80%
Waste data	1	0.40%	0.30%	3.00	9.00%	12.70%
Project data	4	1.60%	1.20%	4.00	12.00%	14.80%

The results indicate that **Operational Data, Sensor Data, and Historical Data** receive the highest final weights among the analyzed data types. These data categories are widely used in Artificial Intelligence applications due to their relevance for monitoring system performance, supporting predictive analytics, and enabling real-time decision-making.

Other data types such as **Customer Data, Market Data, and Textual Data** appear less frequently but still play an important role in specific application areas such as business management and natural language processing tasks.

4.9 Summary of Analytical Findings

This chapter presented a comprehensive analysis of the selected articles using both descriptive and inferential analytical methods. The analysis was conducted in several stages to identify patterns in application domains, analytical techniques, data types, and key research outcomes related to the use of Artificial Intelligence and data analytics in Systems Engineering Management.

The descriptive analysis revealed that Artificial Intelligence applications are distributed across a wide range of engineering and management domains. Among these domains, **project management, supply chain management, construction, and civil engineering** emerged as the most frequently studied areas. This indicates that AI technologies are increasingly being adopted in environments characterized by complex operational systems and high levels of uncertainty.

The analysis of techniques used in the selected studies showed that **Machine Learning and Artificial Intelligence-based methods** are the dominant analytical approaches. These techniques are frequently applied to support predictive analytics, decision-making processes, and operational optimization across different industries.

In terms of data usage, the findings indicate that **operational data, sensor data, and historical data** represent the most commonly used data sources in AI-driven engineering management research. These types of data provide the necessary information for predictive modeling, system monitoring, and performance optimization.

Inferential analysis, including cross-tabulation and chi-square tests, demonstrated statistically significant relationships between several key variables, including **application area, analytical techniques, data types, and reported research outcomes**. These results suggest that the choice of analytical technique and data type is closely related to the specific domain of application.

The content analysis further identified several recurring themes within the literature, including **efficiency improvement, cost reduction, predictive capabilities, process automation, intelligent decision-making, and sustainability**. These themes highlight the primary objectives driving the adoption of Artificial Intelligence technologies in engineering management contexts.

Trend analysis showed that the majority of the selected studies were published in recent years, particularly between **2023 and 2024**, indicating a rapid increase in research interest in this field. This trend reflects the growing importance of AI technologies in addressing complex engineering and management challenges.

Finally, the weighting analysis provided a quantitative assessment of the relative importance of different application domains, techniques, and data types. The results confirmed that **Machine Learning techniques, supply chain and project management applications, and operational data sources** play a central role in current research on AI applications in engineering systems management.

Overall, the findings of this chapter provide a structured understanding of how Artificial Intelligence and data analytics are currently being applied across engineering management domains. These results form the basis for the discussion presented in the next chapter, where the implications of these findings and potential future research directions are examined.

5. Chapter Five : Discussion and Conclusion

5.1 Analysis of Abstract Tables and Coding

The analysis of the abstracts summarized in Table 4.1 provided important insights into the dominant research themes and application domains of Artificial Intelligence in Systems Engineering Management. Through the coding process, several recurring research areas were identified, indicating the primary directions in which AI technologies are being applied within engineering and management contexts.

One of the most prominent themes identified in the reviewed studies is the **application of Artificial Intelligence in construction processes and project management**. A significant portion of the selected articles addresses the use of AI techniques to improve project planning, risk management, resource allocation, and overall project performance. The findings suggest that AI technologies can support project managers by providing predictive insights, optimizing scheduling processes, and improving decision-making in complex project environments.

Several key concepts and codes were identified within this domain, including **project management, risk management, resource optimization, quality control, machine learning techniques, and predictive forecasting**. These concepts reflect the main areas in which AI technologies contribute to improving efficiency and reducing uncertainty in project-based environments.

Another important research area identified in the literature is the **application of Artificial Intelligence in supply chain and materials management**. Many studies emphasize the role of AI technologies in optimizing logistics operations, improving demand forecasting, and enhancing supply chain performance. Machine learning techniques are widely used in this domain to analyze large datasets and generate predictive insights that support better planning and resource allocation. The main coding categories associated with this area include **supply chain management, materials management, demand forecasting, and logistics optimization**.

The analysis also revealed a growing interest in the **automation of engineering processes using Artificial Intelligence**. Several studies highlight the use of AI for system design, modeling, simulation, and optimization. In these applications, AI technologies are used to automate complex engineering tasks and improve system performance through intelligent analysis and predictive modelling. Key coding categories related to this domain include **automation, modeling and simulation, design optimization, and machine learning-based system analysis**.

Among the identified domains, the **application of Artificial Intelligence in construction processes and project management** appears to be the most prominent research focus. This prominence can be explained by several factors. First, a larger number of articles address this domain, indicating strong research interest and availability of relevant literature. Second, AI technologies offer a wide range of applications in project management, including risk assessment, resource allocation, schedule optimization, and quality monitoring. Third, improvements in construction and project management processes can have significant practical implications for reducing costs, improving project quality, and increasing operational efficiency.

Within this primary domain, several important subtopics were identified. These include **risk management, scheduling optimization and resource allocation, quality control and defect detection, and cost forecasting and management**. AI-based approaches in these areas enable more accurate prediction of potential risks, improved allocation of resources, and more efficient monitoring of project performance.

Overall, the coding and classification of the selected studies demonstrate that Artificial Intelligence technologies are increasingly being integrated into engineering management processes to enhance operational efficiency, support predictive decision-making, and automate complex analytical tasks. These findings provide further evidence of the growing importance of AI-driven solutions in modern engineering and project management environments.

5.2 Interpretation of Descriptive Analysis

The descriptive analysis conducted in Chapter 4 provides an overview of the dominant trends in the reviewed literature. The results indicate that **Artificial Intelligence (AI) and Machine Learning (ML)** represent the most frequently used analytical techniques across the selected studies. This finding highlights the central role of machine learning algorithms in supporting predictive modeling, optimization, and decision-support applications in engineering management environments.

The analysis of data types used in the reviewed studies shows that **operational data** is the most commonly utilized data source. This suggests that most Artificial Intelligence applications focus on practical and real-world datasets generated through operational processes, sensors, and system monitoring activities. The prevalence of operational data also reflects the growing emphasis on data-driven decision-making in engineering and management systems.

In terms of application domains, the results reveal that **project management and supply chain management** are the areas with the highest number of published studies. This indicates that researchers and practitioners have shown significant interest in applying Artificial Intelligence technologies to improve planning, coordination, and efficiency in these domains. These sectors often involve complex systems, multiple stakeholders, and large volumes of operational data, making them suitable environments for AI-driven optimization and decision-support solutions.

Overall, the descriptive analysis demonstrates that Artificial Intelligence is increasingly being applied in operational management environments where predictive insights and data-driven optimization can significantly enhance performance and efficiency.

5.3 Interpretation of Mixed Analysis

The mixed analysis conducted in this study, which combines descriptive statistics, cross-tabulation analysis, and inferential statistical testing, provides deeper insights into the relationships between application domains, analytical techniques, and research outcomes.

The results confirm that **Machine Learning remains the most frequently used Artificial Intelligence technique** across the reviewed studies. Machine learning algorithms are widely applied in different domains due to their ability to analyze complex datasets, detect patterns, and generate predictive insights that support decision-making processes.

The analysis also shows that **operational data continues to be the most commonly used data type**, reinforcing the practical nature of AI applications in engineering management. The availability of large volumes of operational data enables organizations to apply predictive analytics techniques for performance monitoring, anomaly detection, and process optimization.

In addition, the results reveal that **efficiency improvement and cost reduction** are among the most frequently reported outcomes in the reviewed studies. These findings indicate that the primary motivation for adopting Artificial Intelligence technologies in engineering management environments is to improve operational performance while reducing resource consumption and project costs.

The analysis also highlights the emerging role of **generative Artificial Intelligence tools such as ChatGPT**, particularly in the domain of project management.

Although its use is still relatively limited compared to traditional AI techniques, ChatGPT has been increasingly applied to support documentation, communication processes, and knowledge management in project-based environments.

The statistical analysis using the **Chi-square test** further confirms that several significant relationships exist between the key variables examined in this study. In all analyses performed, the p-values were below the significance level of 0.05, indicating that the observed associations between variables are statistically significant and unlikely to have occurred by chance.

More specifically, the results suggest that:

- The selection of Artificial Intelligence techniques is influenced by the **application domain** in which they are used.
- The choice of analytical techniques is also related to the **type of data available** for analysis.
- The **outcomes achieved in projects** are influenced by the application domain in which AI technologies are implemented.
- The **results achieved in projects** are also associated with the specific Artificial Intelligence techniques applied.

However, it is important to note that statistical significance does not necessarily imply a direct causal relationship between variables. Other contextual factors, such as organizational characteristics, technological maturity, and data availability, may also influence these relationships.

5.4 Interpretation of Content Analysis

The content analysis conducted in this research identified several recurring themes and conceptual relationships within the reviewed studies. These themes provide insight into the main motivations and expected benefits associated with the adoption of Artificial Intelligence technologies in engineering and management contexts.

One of the most prominent themes identified is the relationship between **Artificial Intelligence and efficiency improvement**. Many studies emphasize the use of AI technologies as tools for enhancing operational efficiency, reducing processing time, and minimizing operational costs across various industries.

Another important theme identified in the literature is the connection between **data analysis and predictive capabilities**. Artificial Intelligence techniques enable organizations to analyze large volumes of data and generate predictive insights that support better planning and decision-making. Predictive analytics is particularly valuable in engineering systems where anticipating future conditions can help prevent failures and optimize resource allocation.

The analysis also highlights the role of **automation and intelligent decision-making**. AI-driven automation can streamline complex processes and reduce the need for manual intervention. By automating repetitive tasks and providing data-driven insights, AI technologies enable organizations to make faster and more informed decisions.

Overall, the results of the content analysis demonstrate that the primary focus of the reviewed studies is the application of Artificial Intelligence technologies to improve operational efficiency, reduce costs, and support intelligent decision-making processes. Additionally, the increasing emphasis on data analysis and predictive modeling indicates that AI is becoming an essential component of modern engineering management practices.

5.5 Interpretation of Trend Analysis

The trend analysis conducted in this study provides important insights into the evolution of research on Artificial Intelligence applications in Systems Engineering Management. The analysis of publication years, presented in Table 4.12 and Figure 4.9, indicates a clear increase in academic interest in this research area over time.

One of the most significant observations is the **rapid growth in the number of publications after 2021**. The number of articles published in 2023 and 2024 is considerably higher than in previous years, indicating a strong increase in research activity related to Artificial Intelligence and its applications in engineering and management systems. This growth reflects the increasing availability of data, advances in computational technologies, and the growing demand for intelligent decision-support systems in complex industrial environments.

Another notable trend is the **growing attention to large language models (LLMs)** such as ChatGPT in recent years. Several recent studies examine the potential of generative AI technologies to support knowledge management, communication, and decision-making processes in areas such as construction management, business administration, and renewable energy systems.

The analysis also shows a **shift toward practical and application-oriented research**. Earlier studies often focused on theoretical discussions of Artificial Intelligence technologies, while more recent research emphasizes real-world implementation and practical use cases in various industries.

Furthermore, the literature indicates an increasing trend toward the **integration of Artificial Intelligence with other digital technologies**, such as the Internet of Things (IoT), Big Data analytics, and Building Information Modeling (BIM). The combination of these technologies enables more advanced data collection, real-time monitoring, and intelligent decision-making capabilities in engineering systems.

Despite the rapid development of this research field, several **research gaps** remain. First, many studies provide general discussions of AI applications but lack **detailed case studies that demonstrate the practical implementation and measurable outcomes of AI technologies in real-world projects**. Second, there is limited research addressing the **practical challenges of implementing Artificial Intelligence systems**, including issues related to implementation costs, data quality, organizational resistance, and technological integration. Finally, the growing adoption of Artificial Intelligence also highlights the need for **ethical standards and governance frameworks** to ensure responsible, transparent, and equitable use of AI technologies.

Overall, the trend analysis confirms that Artificial Intelligence research in engineering management is expanding rapidly and is expected to continue growing as digital transformation accelerates across industries.

5.6 Interpretation of Weighting Analysis Results

The weighting analysis conducted in this study provides a quantitative evaluation of the relative importance of different application domains, analytical techniques, and data types identified in the reviewed literature. The weighting results highlight the key areas where Artificial Intelligence technologies are most frequently applied and where they demonstrate the greatest impact.

The results indicate that **Machine Learning has the highest weight among the analyzed techniques**, accounting for approximately 28.64% of the total weight. This finding confirms that machine learning algorithms represent the most widely used and influential Artificial Intelligence methods in engineering management research. Machine learning techniques are particularly effective for predictive analytics, optimization, and pattern recognition tasks, which explains their widespread adoption across different industries.

In terms of application domains, the analysis shows that **energy systems, supply chain management, and construction-related applications** receive relatively high weights. These domains often involve complex operational systems, large datasets, and dynamic environments, making them well suited for Artificial Intelligence-based analytical approaches. The increasing attention given to energy-related applications also reflects the growing importance of sustainability and efficient resource management in modern engineering systems.

The weighting analysis also highlights the importance of selecting appropriate analytical techniques depending on the characteristics of the problem being addressed. While machine learning techniques are widely applicable across multiple domains, other methods such as **deep learning, natural language processing (NLP), and advanced data analytics techniques** play important roles in more specialized analytical tasks, including image recognition, text analysis, and complex pattern detection.

In addition to analytical techniques, the results emphasize the importance of **data availability and quality** in Artificial Intelligence applications. The analysis shows that **operational data, sensor data, historical data, and customer-related datasets** are among the most frequently used data sources in the reviewed studies. Operational and sensor data are particularly important for real-time monitoring and performance analysis, while historical data enables predictive modeling and trend analysis. Customer-related data is often used to support decision-making processes and improve service design.

Overall, the weighting analysis confirms that successful Artificial Intelligence applications in engineering management depend on the **combined interaction of appropriate analytical techniques, relevant application domains, and high-quality data sources**. These findings provide useful insights for researchers and practitioners seeking to implement Artificial Intelligence technologies in complex engineering and management environments.

6. Chapter Six : Final Results and Recommendations

6.1 Introduction

The rapid development of Artificial Intelligence (AI) and machine learning technologies has significantly influenced modern engineering and management systems. These technologies provide new opportunities for improving decision-making, optimizing operational processes, and increasing efficiency across various industries. As organizations increasingly rely on data-driven approaches, understanding how AI can support complex engineering and management systems has become an important research topic.

The main objective of this study was to systematically review the applications of Artificial Intelligence and machine learning across different engineering and management domains. Through a systematic literature review of selected studies, this research aimed to identify major research trends, key application areas, commonly used analytical techniques, and existing research gaps in the field.

To achieve this objective, a structured and evidence-based methodology was employed. A total of 73 peer-reviewed articles were selected and analyzed using several analytical approaches, including descriptive analysis, cross-tabulation analysis, Chi-square statistical testing, content analysis, trend analysis, and weighting analysis. These analytical methods allowed for a comprehensive examination of the relationships between application domains, analytical techniques, data types, and research outcomes.

This chapter summarizes the key findings of the study and provides an integrated interpretation of the results obtained in the previous chapters. In addition, the chapter highlights the main contributions of the research, discusses the practical implications of the findings, and identifies directions for future research in the field of Artificial Intelligence applications in engineering management systems.

6.2 Overview of Selected Articles

The analysis of the selected articles provides valuable insights into the development and evolution of research related to Artificial Intelligence and machine learning applications. The trend analysis presented in Table 4.12 and Figure 4.9 clearly shows a significant increase in the number of publications in recent years.

In the earlier years of the reviewed period, particularly in 2014, 2018, and 2020, the number of published studies was relatively low. This reflects the early stages of research activity in this field and the limited adoption of Artificial Intelligence technologies during that time. However, beginning in 2021, a steady growth in the number of publications can be observed, followed by a sharp increase in 2023 and 2024. The year 2024 represents the peak of publication activity with 17 articles, indicating a strong acceleration in research interest and practical adoption of Artificial Intelligence technologies.

This rapid growth can be attributed to several factors, including technological advancements in Artificial Intelligence, increased availability of large datasets, and growing awareness of the potential of AI technologies for solving complex engineering and management problems.

Further analysis of the selected articles, summarized in Table 4.1, reveals that **project management and supply chain management** are the most frequently studied application domains. These areas have attracted considerable attention because they involve complex decision-making processes, dynamic environments, and large volumes of operational data. Artificial Intelligence technologies provide valuable tools for optimizing planning processes, improving resource allocation, and enhancing operational efficiency in these domains.

In addition to these areas, other application domains such as **energy systems, construction, and pandemic management** have also received significant research attention. The diversity of these application areas demonstrates the wide applicability of Artificial Intelligence technologies in addressing challenges across multiple industries.

The review also indicates that **Artificial Intelligence and Machine Learning techniques** are the most frequently used analytical approaches in the selected studies. These techniques play a crucial role in data analysis, predictive modeling, and optimization processes. Other analytical techniques, including deep learning, natural language processing, and advanced data analytics, are also applied in various studies, although with lower frequency.

Finally, the analysis of data types used in the reviewed studies shows that **operational data** represents the most commonly used data source. Operational data reflects real-world system performance and provides valuable information for analyzing processes, identifying patterns, and predicting future outcomes. Other data types such as historical data, sensor data, and customer-related data are also used in the literature, although to a lesser extent.

Overall, the analysis of the selected articles demonstrates the growing importance of Artificial Intelligence technologies in supporting data-driven decision-making and improving the management of complex engineering systems.

6.4 Weighting Analysis

6.4.1 Methodology

To determine the relative importance of the identified application domains, analytical techniques, and data types, a weighting analysis method was applied. This approach assigns a weighted score to each element based on its occurrence and importance within the reviewed literature.

Three criteria were used to calculate the final weights:

1. **Frequency Weight (40%)** – based on the number of articles that mentioned each item.
2. **Keyword Weight (30%)** – based on the frequency with which each item appeared as a keyword in the reviewed articles.
3. **Impact Weight (30%)** – based on the perceived influence of each item on the outcomes and contributions of the reviewed studies, evaluated with the input of expert reviewers.

By combining these three criteria, a final weighted score was calculated for each domain, technique, and data type.

6.4.2 Results of the Weighting Analysis

The results of the weighting analysis highlight several key areas and techniques that play a dominant role in the reviewed literature.

Among the analytical techniques, **machine learning achieved the highest weight (28.64%)**, indicating its central role in Artificial Intelligence research and applications. Machine learning algorithms are widely applied due to their flexibility and effectiveness in handling large datasets and solving complex optimization and prediction problems.

Other important techniques identified include **deep learning (14.30%)**, **natural language processing (15.50%)**, and **data analytics (14.05%)**. These techniques are frequently used in specialized analytical tasks such as image recognition, text analysis, and advanced data processing.

In terms of application domains, the analysis shows that **energy systems, supply chain management, construction, and pandemic management** have relatively high weights. These domains often involve complex operational systems and large volumes of data, making them suitable environments for Artificial Intelligence applications.

The analysis also examined the types of data most frequently used in Artificial Intelligence applications. The results indicate that **operational data (20.45%)** is the most commonly used data type, reflecting the practical focus of many AI applications. Operational data provides valuable information about system performance and real-world processes.

Other important data sources include **sensor data (18.30%)**, which is commonly used for real-time monitoring and environmental data collection; **historical data (15.35%)**, which supports predictive modeling and trend analysis; and **customer data (16.45%)**, which helps organizations better understand user behavior and improve service delivery.

6.4.3 Interpretation of the Results

The results of the weighting analysis confirm the **dominant role of machine learning techniques** in Artificial Intelligence research and applications across multiple industries. These techniques provide powerful tools for analyzing large datasets, identifying patterns, and supporting data-driven decision-making.

The analysis also highlights the importance of specific application domains, particularly **energy systems, supply chain management, and construction**, where Artificial Intelligence technologies are increasingly used to optimize operational processes and improve system performance.

Additionally, the results emphasize the importance of selecting appropriate **data types and analytical techniques** based on the specific characteristics of the problem being addressed. Operational, sensor, and historical data play critical roles in enabling effective Artificial Intelligence applications.

Overall, the findings demonstrate that successful implementation of Artificial Intelligence technologies depends on the **combined interaction of appropriate techniques, relevant application domains, and high-quality data sources**.

6.5 Content Analysis

6.5.1 Frequent Keywords

The content analysis of the selected articles revealed several frequently occurring keywords that reflect the primary research focus in the field. The most commonly identified keywords include **Artificial Intelligence, Machine Learning, Data, Improvement, Efficiency, Management, Optimization, Prediction, Supply Chain, and Energy**.

These keywords indicate that current research is strongly centered on the use of Artificial Intelligence technologies to analyze data, optimize processes, and improve operational efficiency in complex engineering and management environments. The frequent occurrence of terms related to optimization and prediction also highlights the importance of AI-driven decision support systems in modern industrial applications.

6.5.2 Main Themes

The analysis of article descriptions allowed the identification of several major themes that characterize the current research landscape.

One of the most prominent themes is the **application of Artificial Intelligence across various industries**. Many studies examine the use of AI technologies in fields such as supply chain management, energy systems, construction management, and project management. These studies demonstrate the wide applicability of AI in solving complex operational problems and improving system performance.

Another key theme identified in the literature is **efficiency improvement and cost reduction**. Many researchers emphasize the role of Artificial Intelligence in optimizing processes, reducing operational costs, and increasing productivity across different industries.

The theme of **data analysis and predictive modeling** is also highly prominent. Artificial Intelligence techniques are frequently used to analyze large datasets and identify patterns that enable the prediction of future trends and system behavior. This predictive capability is particularly valuable for improving planning and risk management processes.

Process automation represents another important theme. Several studies highlight the use of AI technologies to automate repetitive and complex tasks, reducing human intervention and increasing operational accuracy.

In addition, **intelligent decision-making** is widely discussed in the literature. AI-based decision support systems enable organizations to analyze complex information and make more informed strategic decisions.

Finally, a number of studies address the relationship between Artificial Intelligence and **sustainability and sustainable development**. In these studies, AI technologies are used to improve energy efficiency, optimize resource usage, and support environmentally sustainable practices.

6.5.3 Relationships between Themes

The content analysis also revealed important connections between the identified themes. These relationships help explain how Artificial Intelligence technologies contribute to improvements in engineering and management systems.

One important relationship is the connection between **Artificial Intelligence and efficiency improvement**. AI technologies are frequently used as tools to enhance operational performance, reduce processing time, and minimize costs across various industries.

Another key relationship is observed between **data analysis and predictive capabilities**. By analyzing large volumes of data, Artificial Intelligence techniques enable organizations to forecast future conditions, identify potential risks, and support proactive decision-making.

Additionally, the relationship between **automation and intelligent decision-making** is evident in many studies. Automated AI systems can analyze data and generate recommendations, enabling organizations to make faster and more effective decisions in complex environments.

6.6 Trend Analysis

The trend analysis conducted in this study indicates a significant increase in research attention toward Artificial Intelligence technologies in recent years. The number of published articles related to AI applications has grown rapidly, reflecting the expanding interest of researchers and practitioners in this field.

In particular, recent years have witnessed increasing attention to **large language models (LLMs)** such as ChatGPT and their potential applications in various domains, including construction management, business administration, and renewable energy systems. This development represents an important emerging trend in Artificial Intelligence research.

Another notable trend is the growing emphasis on **practical applications of Artificial Intelligence**. While earlier studies often focused on theoretical aspects of AI technologies, more recent research concentrates on real-world implementation and industrial use cases.

Furthermore, the literature indicates an increasing trend toward the **integration of Artificial Intelligence with other digital technologies**, such as the Internet of Things (IoT), Big Data analytics, and Building Information Modeling (BIM). The integration of these technologies creates new opportunities for intelligent monitoring systems, predictive analytics, and advanced decision-support platforms.

Overall, the trend analysis demonstrates that Artificial Intelligence is becoming an essential component of modern engineering and management systems.

6.7 Research Gaps

Despite the rapid development of Artificial Intelligence applications, the systematic review identified several important research gaps that require further investigation.

One of the most notable gaps is the **limited availability of in-depth case studies**. Many studies provide general discussions of AI applications but lack detailed analyses of real-world implementations and measurable outcomes. More empirical research is needed to demonstrate the practical effectiveness of AI technologies in operational environments.

Another important gap concerns the **challenges associated with implementing Artificial Intelligence systems**. Issues such as implementation costs, lack of access to high-quality data, technological integration difficulties, and resistance to organizational change are often mentioned but not sufficiently explored in the literature.

In addition, the increasing use of Artificial Intelligence raises significant **ethical and governance considerations**. As AI systems become more integrated into decision-making processes, there is a growing need to develop ethical standards and regulatory frameworks that ensure responsible, transparent, and equitable use of these technologies.

Overall, the findings of this systematic review demonstrate that Artificial Intelligence is rapidly becoming a key enabling technology across multiple industries. While significant progress has been made in applying AI for process optimization and efficiency improvement, further research is required to address existing challenges and fully realize the potential of these technologies.

6.8 The AI-SEM Maturity Matrix Framework

To synthesize the findings of this research and provide a structured interpretation of Artificial Intelligence adoption in Systems Engineering Management (SEM), this study proposes the **AI-SEM Maturity Matrix**. The matrix serves as a conceptual framework for classifying AI applications according to two dimensions: (1) the scope of their application across Systems Engineering Management activities, and (2) the technological depth and automation level of the Artificial Intelligence techniques employed.

The framework is designed as a **four-by-four conceptual matrix** that illustrates how AI applications evolve from basic monitoring and descriptive analytics toward advanced autonomous systems capable of supporting strategic decision-making across engineering organizations.

By integrating these two dimensions, the AI-SEM Maturity Matrix provides a structured way to evaluate the maturity of AI adoption, identify where existing research is concentrated, and highlight underexplored areas for future development. The matrix therefore functions both as a **synthesis of the reviewed literature and as a roadmap for future research and practical implementation** of Artificial Intelligence in Systems Engineering Management.

6.8.1 Axis X (Horizontal): Application Scope in Systems Engineering Management

The horizontal axis represents the **application scope of Artificial Intelligence across Systems Engineering Management activities**. It reflects the progression from operational execution tasks toward higher-level strategic management functions.

Operational / Execution Level

At the operational level, Artificial Intelligence is primarily used for real-time monitoring, anomaly detection, and automated responses based on immediate system inputs. Applications typically rely on high-frequency operational data generated by sensors, industrial equipment, and system logs.

Typical examples include real-time equipment monitoring, automated fault detection, and early anomaly identification. These applications primarily aim to improve operational reliability and enable continuous system monitoring.

Process Optimization Level

The process optimization level represents the next stage of maturity, where Artificial Intelligence is used to improve the efficiency and performance of operational workflows. At this stage, AI technologies integrate data from multiple operational sources to optimize performance metrics across interconnected processes.

Typical applications include predictive scheduling of operations, demand forecasting, supply chain optimization, and energy consumption optimization. These applications support process-level decision-making and contribute to improved operational efficiency.

System Design and Planning Level

At the system design and planning level, Artificial Intelligence supports engineering design activities, simulation analysis, and long-term planning processes. AI systems can integrate data from design tools, simulation environments, and historical performance databases in order to evaluate system performance prior to implementation.

Typical applications include generative design exploration, simulation parameter optimization, predictive quality evaluation, and lifecycle cost modeling. These applications help engineers improve system design quality and reduce risks during early stages of system development.

Strategic Management Level

The strategic management level represents the highest application scope within Systems Engineering Management. At this stage, Artificial Intelligence supports long-term strategic decision-making and enterprise-level resource allocation.

AI systems integrate data from multiple organizational domains, including financial data, market intelligence, customer feedback, and regulatory information. Typical applications include strategic asset portfolio optimization, capital investment planning, enterprise risk analysis, and long-term system lifecycle management.

6.8.2 Axis Y (Vertical): Technological Depth and Automation Level

The vertical axis represents the **technological sophistication and automation capability of Artificial Intelligence techniques**. It reflects the progression from basic analytical support toward autonomous intelligent systems capable of adaptive decision-making.

Level 1: Descriptive / Diagnostic Analytics

This level represents the initial stage of data-driven decision support, where organizations rely primarily on analytical tools to understand past events and monitor system conditions.

Typical tools include statistical analysis, rule-based systems, dashboards, and threshold-based alert mechanisms. These systems provide situational awareness and monitoring capabilities but do not perform predictive or autonomous decision-making.

Level 2: Predictive Machine Learning

At the predictive level, machine learning models are used to forecast future system behavior based on historical data patterns. These models enable proactive decision-making by predicting system failures, demand patterns, or performance degradation.

Typical techniques include Random Forest models, Support Vector Machines, regression models, and neural networks trained on structured datasets. Outputs may include failure probability estimates, Remaining Useful Life predictions, and operational forecasting.

Level 3: Prescriptive / Cognitive Artificial Intelligence

At this stage, Artificial Intelligence systems analyze complex datasets and provide recommendations or optimized actions based on system constraints.

Techniques commonly used at this level include deep learning models, Natural Language Processing (NLP), Bayesian networks, and advanced optimization algorithms. These systems enable prescriptive decision support by identifying optimal actions based on analytical insights.

Level 4: Autonomous / Self-Learning Systems

The highest maturity level is characterized by autonomous Artificial Intelligence systems capable of continuous learning and adaptive decision-making. These systems update their internal models using real-time feedback and operate with minimal human intervention.

Typical technologies include reinforcement learning, AIOps platforms, federated learning, and self-supervised learning architectures. At this level, AI systems can autonomously manage complex operational environments and optimize system performance dynamically.

6.9 The AI-SEM Maturity Matrix Visualization

Figure 6.X presents the proposed **AI-SEM Maturity Matrix**, which integrates the two dimensions described above: application scope in Systems Engineering Management (horizontal axis) and technological depth or automation level (vertical axis).

By positioning Artificial Intelligence applications within this matrix, organizations and researchers can better understand the maturity level of AI adoption and identify pathways for further development.

The diagonal of the matrix highlights four major maturity zones representing the progressive evolution of Artificial Intelligence adoption within engineering management systems

Table 6.1Proposed AI-SEM Maturity Matrix

Technological Depth / Automation Level	**Operational / Execution**	**Process Optimization**	**System Design & Planning**	**Strategic Management**
Level 4 – Autonomous / Self-Learning	Autonomous monitoring	Autonomous process control	AI-driven generative design	**Zone 4: Intelligent Management**
Level 3 – Prescriptive / Cognitive	AI-assisted recommendations	Process optimization by advanced AI	**Zone 3: Insight Generation**	Strategic AI decision support
Level 2 – Predictive	Predictive maintenance	**Zone 2: Performance Prediction**	Predictive performance modelling	Strategic forecasting
Level 1 – Descriptive / Diagnostic	**Zone 1: Foundational Monitoring**	Process reporting	Design analysis support	Strategic dashboards

6.9.1 Detailed Zone Analysis

Based on the interaction between the two axes, four major maturity zones can be identified.

Zone 1: Foundational Monitoring (X1, Y1)

This zone represents the initial stage of Artificial Intelligence adoption. Organizations operating at this level focus primarily on data collection, monitoring systems, and anomaly detection capabilities. Typical implementations include SCADA monitoring systems, operational dashboards, and rule-based alert mechanisms.

Zone 2: Performance Prediction (X2, Y2)

Zone 2 represents the most common level of Artificial Intelligence application identified in the reviewed literature. At this stage, machine learning models are used to predict system failures, forecast operational parameters, and improve short-term decision-making processes. Many predictive maintenance and forecasting studies fall within this category.

Zone 3: Insight Generation (X3, Y3)

Zone 3 represents a transition from predictive analytics toward deeper analytical insight generation. AI systems at this level analyze complex datasets and provide actionable insights that influence engineering design decisions, operational planning, and system optimization strategies.

Examples include Natural Language Processing analysis of maintenance reports and simulation-based optimization of engineering designs.

Zone 4: Intelligent Management (X4, Y4)

Zone 4 represents the highest maturity level of Artificial Intelligence adoption within Systems Engineering Management. At this stage, AI systems integrate data from multiple organizational domains and support autonomous strategic decision-making.

Examples include reinforcement learning systems for enterprise asset management optimization and cross-domain decision-support platforms that integrate operational, financial, and strategic data.

Although the four major zones are illustrated along the diagonal of the matrix, Artificial Intelligence applications may also appear in intermediate positions depending on their application scope and technological sophistication.

6.10 Research Landscape Mapping and Identified Gaps

When the reviewed literature is mapped onto the AI-SEM Maturity Matrix, a clear concentration pattern emerges.

First, the majority of existing studies are located within **Zone 2 (Performance Prediction)**. These studies primarily apply machine learning techniques to structured operational data in order to predict system failures, estimate Remaining Useful Life, and optimize operational performance.

Second, a smaller but growing number of studies are beginning to move toward **Zone 3 (Insight Generation)**. These studies apply advanced Artificial Intelligence methods such as deep learning and Natural Language Processing to analyze heterogeneous datasets and generate deeper analytical insights.

However, the upper-right region of the matrix corresponding to **Zone 4 (Intelligent Management)** remains largely underexplored. While conceptual frameworks for autonomous decision-making systems exist, empirical evidence demonstrating fully integrated, cross-domain AI systems capable of supporting strategic engineering management decisions is still limited.

This distribution suggests that current research is primarily concentrated on predictive operational applications, while autonomous and strategically integrated Artificial Intelligence systems remain a significant opportunity for future research.

6.10.1 Identified Research Opportunities

The gaps identified through the AI-SEM Maturity Matrix highlight several important directions for future research.

Bridging the Gap Between System Design and Strategic Management

Future research should investigate methods capable of translating high-level strategic objectives into operational and design-level constraints that can be executed by prescriptive AI models. This would enable stronger integration between engineering design processes and strategic organizational decision-making.

Data Integration for Autonomous Systems

Achieving higher levels of AI maturity requires robust integration of heterogeneous data sources, including operational sensor data, engineering design information, financial data, and market intelligence. Future research should therefore explore Artificial Intelligence architectures capable of reliably integrating these diverse data types.

Trust and Explainability in High-Impact Decisions

As Artificial Intelligence systems increasingly influence strategic decisions, explainable AI frameworks become essential. Future research should focus on developing transparent AI models capable of providing interpretable reasoning for decisions that may involve significant financial or operational consequences.

6.11 Conclusion and Recommendations

The AI-SEM Maturity Matrix proposed in this research provides a structured framework for evaluating the maturity of Artificial Intelligence adoption within Systems Engineering Management. By combining the dimensions of application scope and technological depth, the matrix allows researchers and practitioners to classify AI applications, identify maturity levels, and recognize pathways for future development.

From a practical perspective, the framework can serve as a diagnostic tool for organizations seeking to strengthen their Artificial Intelligence capabilities.

Organizations operating in Zone 1 should prioritize the development of reliable data infrastructures and monitoring systems.

Organizations located in Zone 2 should expand predictive analytics capabilities and extend AI applications toward design and planning activities.

Organizations aiming to achieve Zone 4 will require significant investment in cross-domain data integration, autonomous decision-making algorithms, and trustworthy Artificial Intelligence governance frameworks.

From an academic perspective, the AI-SEM Maturity Matrix demonstrates that although Artificial Intelligence is already widely applied for predictive analytics and operational optimization, the vision of fully autonomous and strategically intelligent engineering management systems remains largely unexplored.

Consequently, this area represents a critical frontier for both academic research and industrial innovation in the coming years.

7. Chapter 7: Conclusions and Future Research Directions

7.1 Summary of the Research

This research investigated the role of **Artificial Intelligence (AI) and data analytics in optimizing Systems Engineering Management (SEM) processes**. With the increasing complexity of engineering systems and the growing availability of large volumes of data, organizations require advanced analytical tools capable of improving decision-making, efficiency, and operational performance. Artificial Intelligence technologies, particularly machine learning and data-driven analytical methods, offer significant potential for addressing these challenges.

To explore this potential, a **Systematic Literature Review (SLR)** methodology was adopted. Through a structured and transparent selection process, a total of **73 peer-reviewed studies** published between **2014 and 2025** were identified and analyzed. The selected studies covered multiple domains, including project management, supply chain management, construction engineering, energy systems, and other engineering applications.

The analysis included several complementary approaches, including **descriptive analysis, statistical analysis, content analysis, trend analysis, and weighting analysis**. These analytical methods allowed for the identification of dominant research themes, frequently used Artificial Intelligence techniques, commonly used data types, and emerging research trends.

The findings demonstrate that Artificial Intelligence technologies are increasingly being integrated into engineering management processes to support **predictive analysis, process optimization, and data-driven decision making**.

7.2 Key Research Findings

The results of the systematic review and subsequent analyses revealed several important insights.

First, **machine learning techniques** were identified as the most frequently applied Artificial Intelligence methods across the reviewed studies. These techniques have been widely used for predictive maintenance, demand forecasting, risk assessment, and resource allocation.

Second, **operational data** was found to be the most commonly used type of data in Artificial Intelligence applications within engineering systems. This indicates that most current implementations focus on practical operational improvements rather than purely theoretical applications.

Third, the analysis showed that **project management and supply chain management** are among the most frequently studied application domains. These areas involve complex operational systems and large volumes of data, making them particularly suitable for the implementation of Artificial Intelligence-based decision support systems.

Fourth, the results of the statistical analysis, particularly the **Chi-square test**, demonstrated statistically significant relationships between several key variables, including the type of Artificial Intelligence technique used, the application domain, the type of data analyzed, and the outcomes achieved. These findings suggest that the selection of appropriate AI techniques depends strongly on the context in which they are applied.

Finally, the **trend analysis** revealed a substantial increase in research activity in the field of Artificial Intelligence applications since 2021, with a peak in publications observed in 2024. This trend reflects the rapid technological advancement of AI technologies and the growing interest in their practical applications.

7.3 Research Contributions

This study makes several contributions to the field of Systems Engineering Management and Artificial Intelligence research.

First, it provides a **comprehensive synthesis of existing research** on Artificial Intelligence applications in engineering management through a structured systematic literature review.

Second, the research identifies the **most commonly used AI techniques, data types, and application domains**, providing a clearer understanding of the current state of research in this field.

Third, this study introduces the **AI-SEM Maturity Matrix**, a conceptual framework that maps Artificial Intelligence applications according to their **application scope within the engineering lifecycle and their technological depth or automation level**. This framework provides a structured perspective for evaluating the maturity of Artificial Intelligence adoption in engineering systems management.

Fourth, the research identifies **key research gaps and future research opportunities**, particularly in the area of autonomous and strategic AI-driven decision-making systems.

Together, these contributions provide both **academic value and practical insights** for researchers and organizations interested in integrating Artificial Intelligence technologies into engineering management systems.

7.4 Research Limitations

Despite the rigorous methodology employed in this study, several limitations should be acknowledged.

First, the systematic review was limited to **English and Persian language publications**, which may have excluded relevant research published in other languages.

Second, although multiple academic databases were used, some relevant industry reports or proprietary research studies may not have been accessible due to database access restrictions.

Third, the rapid development of Artificial Intelligence technologies means that new studies may emerge after the completion of the literature review, potentially influencing the research landscape.

Finally, while statistical and content analyses were performed, the study relied primarily on **secondary data from existing literature**, and therefore did not include primary empirical validation through industrial case studies.

7.5 Recommendations for Future Research

The findings of this research highlight several important directions for future studies.

First, future research should focus on **empirical case studies and real-world implementations** of Artificial Intelligence systems in engineering management environments. Such studies would provide deeper insights into the practical challenges and benefits of AI adoption.

Second, further research is needed to explore the **integration of Artificial Intelligence with other emerging technologies**, including the Internet of Things (IoT), digital twins, and advanced simulation tools.

Third, as Artificial Intelligence systems increasingly influence critical engineering decisions, future research should address issues related to **explainable AI (XAI), transparency, and ethical considerations** in automated decision-making systems.

Finally, additional research is needed to explore the development of **fully autonomous AI-driven management systems**, particularly within the context of complex engineering infrastructures.

7.6 Final Remarks

Artificial Intelligence is rapidly transforming the field of engineering systems management by enabling more efficient, data-driven, and intelligent decision-making processes. While significant progress has already been made in areas such as predictive maintenance and operational optimization, the full potential of Artificial Intelligence in strategic engineering management remains largely unexplored.

The framework and findings presented in this study demonstrate that Artificial Intelligence has the potential to become a **central enabling technology for future engineering systems**, supporting more resilient, efficient, and adaptive management processes.

Continued research and technological development in this field will play a crucial role in shaping the next generation of intelligent engineering management systems.

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