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# AI-Enabled Digital Engineering for Complex Systems: An Industry-Oriented Framework for Decision-Making and Integration

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## Abstract

Engineering failures and poor system-level decisions continue to cost industries billions annually, often driven by fragmented data environments, disconnected tools, and limited integration across complex systems. As organizations adopt digital engineering practices, the inability to effectively integrate artificial intelligence within these environments remains a critical gap, leading to inconsistent decision-making, reduced traceability, and inefficiencies across the system lifecycle. Current approaches frequently apply AI as a standalone analytical capability, failing to connect insights with engineering processes and limiting its practical impact. This study addresses this challenge by proposing an industry-oriented framework that integrates AI within digital engineering to support system-level decision-making and lifecycle coherence. The framework aligns AI-driven analytics with model-based systems engineering principles, enabling structured integration across design, validation, and operational phases. Key elements include enhanced traceability, improved interoperability, and decision support mechanisms that link data, models, and engineering workflows. The contribution of this research lies in providing a practical and scalable approach for embedding AI into digital engineering environments. The proposed framework supports improved decision consistency, strengthens system integration, and enhances the effectiveness of engineering processes. The findings offer actionable insights for industry practitioners seeking to transition toward more integrated, intelligent, and data-driven engineering systems.

## Keywords
Artificial Intelligence, Digital Engineering, Systems Engineering, Decision-Making, Complex Systems.

## 1. Introduction
Complex engineering systems are increasingly developed through distributed teams, heterogeneous tools, large data sources, and accelerated lifecycle demands. In many industrial environments, requirements, system models, simulation outputs, operational data, and decision records remain separated across different platforms. This fragmentation limits traceability, slows engineering decisions, and weakens the connection between system design, validation, and operational performance. As a result, organizations may experience rework, inconsistent decisions, delayed verification, and reduced confidence in system-level outcomes.

Digital engineering has been introduced to address these challenges by improving model continuity, data accessibility, lifecycle traceability, and system integration. However, many digital engineering implementations remain focused on tool adoption rather than decision support. Models and data may exist in digital form, but they are not always connected to analytical methods that can evaluate alternatives, detect performance patterns, or support timely engineering judgment. This gap is important for complex systems because system behavior often depends on interactions among requirements, architecture, interfaces, verification evidence, and operational conditions.

Artificial intelligence can support digital engineering by analyzing large engineering datasets, identifying trends, detecting anomalies, supporting predictive assessment, and improving the comparison of design or operational alternatives. Its value is limited, however, when AI is used as an isolated analytical function outside the engineering workflow. In that case, AI output may not be traceable to requirements, connected to system models, or linked to validation decisions. A practical integration approach is therefore needed so that AI-driven insights can move through a structured data-to-model-to-decision pathway.

This paper proposes an industry-oriented framework for integrating AI within digital engineering environments for complex systems. The framework connects data integration, model integration, AI-enabled analytics, and decision support within a lifecycle feedback structure. By linking AI outputs to engineering artifacts and decision criteria, the proposed approach supports improved traceability, interoperability, decision speed, and decision accuracy. The paper also includes a weighted multi-criteria evaluation to compare a traditional engineering environment with an AI-enabled digital engineering environment and to demonstrate the potential improvement in system-level decision performance.

### 1.1 Objectives

The objectives of this research are as follows:

1) To identify key limitations in traditional and partially digital engineering environments, especially fragmented data, disconnected models, weak traceability, and isolated decision processes.
2) To propose an AI-enabled digital engineering framework that links engineering data, system models, AI analytics, and decision support across the system lifecycle.
3) To explain how AI contributes to engineering improvement through predictive analysis, anomaly detection, optimization support, and feedback between data, models, and decisions.
4) To evaluate the proposed framework using a weighted multi-criteria decision model based on traceability, integration, decision speed, and accuracy.
5) To provide practical guidance for industry practitioners seeking to move from isolated AI tools toward integrated, traceable, and decision-focused digital engineering workflows.

## 2. Literature Review

Complex engineering environments have become more difficult to manage as systems include more software, data, interfaces, stakeholders, and lifecycle dependencies. In traditional engineering practice, requirements, architecture models, simulation results, operational data, and decision records are often maintained in separate tools. This separation reduces system-level visibility and makes it harder to maintain traceability between design intent, verification evidence, and operational outcomes. In large industrial programs, these gaps can affect schedule performance, validation quality, and decision consistency because engineering teams must interpret disconnected information across multiple platforms (NASA 2020). Similar challenges are observed in aerospace engineering, where digital transformation efforts depend on stronger model continuity and lifecycle coordination (Airbus 2024). Boeing (2024) also emphasized the role of digital engineering and model-based transformation in improving integration across complex aerospace programs.

Digital engineering has been introduced to improve these conditions by replacing document-centered processes with model-centered and data-connected engineering practices. A key concept within this area is the digital thread, which supports the flow of authoritative technical information across requirements, design, analysis, verification, production, and operation. Digital twin approaches extend this capability by connecting virtual system representations with operational or simulation data, allowing engineers to monitor performance, evaluate alternatives, and support lifecycle decisions (Tao et al. 2019). However, many digital engineering implementations remain focused on tool deployment instead of decision execution. When digital models are not connected to clear decision criteria, feedback loops, and validation evidence, the practical value of digital engineering is limited (Madni and Sievers 2018).

Model-Based Systems Engineering provides a technical foundation for organizing system information in a structured and traceable form. MBSE supports the formal representation of requirements, functions, interfaces, behavior, constraints, and verification relationships within a model-based environment. SysML is widely used for representing system architecture, behavior, parametric relationships, and requirement traceability in complex engineering applications (Object Management Group 2017). Prior work has shown that MBSE can improve communication among engineering teams, reduce fragmentation across artifacts, and support more consistent lifecycle analysis (Friedenthal et al. 2014). Estefan (2008) also showed that model-based methods can support system integration, architecture evaluation, and verification planning in complex engineering applications.

Artificial intelligence has added new capability to engineering analysis by supporting pattern recognition, predictive assessment, anomaly detection, optimization, and decision support across large technical datasets. In industrial systems, AI-based methods have been applied to manufacturing analytics, design evaluation, maintenance prediction, and operational forecasting (Lee et al. 2018). These methods can improve decision speed and accuracy when they are connected to relevant engineering data and system performance criteria. However, AI is often implemented as a separate analytical layer rather than as part of the engineering workflow. In such cases, AI outputs may not be traceable to requirements, linked to system models, or validated against lifecycle objectives (Rasheed et al. 2020). This limits the ability of AI to support reliable system-level decisions.

The literature indicates that digital engineering, MBSE, digital twins, and AI each provide important value for complex systems, but their combined use is still not fully mature in many industrial settings. Digital engineering improves lifecycle connectivity, MBSE provides structured system representation, and AI supports data-driven analysis and prediction. The remaining gap is the lack of a practical framework that connects engineering data, system models, AI-enabled analytics, and decision support in a traceable workflow. This paper addresses that gap by proposing an industry-oriented AI-enabled digital engineering framework and evaluating its decision-support value using weighted system performance criteria.

## 3. Methods

This study develops an industry-oriented framework for integrating artificial intelligence within digital engineering environments. The method combines conceptual framework development with a weighted multi-criteria evaluation model to compare traditional engineering practice with an AI-enabled digital engineering approach.

The proposed framework includes four connected layers: data integration, model integration, AI-enabled analytics, and decision support. The data integration layer includes requirements, historical data, sensor data, simulation outputs, and operational records. The model integration layer connects system architecture models, SysML models, simulation models, and verification artifacts. The AI-enabled analytics layer supports predictive analysis, optimization, anomaly detection, and pattern recognition. The decision support layer uses these outputs to support trade studies, validation actions, and system-level decisions.

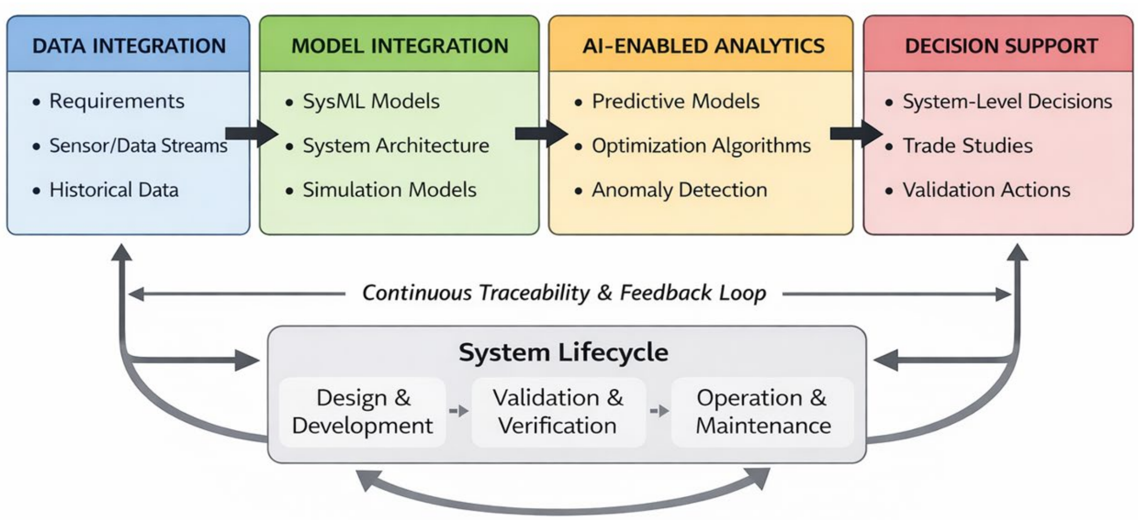


Figure 1. AI-Enabled Digital Engineering Framework.

Figure 1 shows how engineering data, system models, AI analytics, and decision support are connected through a continuous traceability and feedback loop. The framework places AI inside the engineering workflow rather than treating it as a separate analysis tool. In this structure, AI supports decision improvement by using integrated data and models to strengthen traceability, improve integration, support faster trade studies, and increase confidence in validation decisions.

A weighted multi-criteria decision model is used to evaluate the framework. The model combines multiple performance criteria into one overall score:

$$Score = \sum_{i=1}^{n} w_i \, x_i$$

where:

$w_i$ = weight of criterion

$x_i$ = normalized performance score

n = number of evaluation criteria

To ensure comparability across criteria, performance scores are normalized as:

$$x_i^{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

This formulation supports objective aggregation of multi-criteria performance metrics within the digital engineering decision space.

## 4. Data Collection

The data for this study are based on a structured comparative assessment of two engineering scenarios. The first scenario represents a traditional engineering environment where data, models, tools, and decision records are partially disconnected. The second scenario represents an AI-enabled digital engineering environment where data, models, analytics, and decision support are linked through the proposed framework.

Four criteria are used for evaluation: traceability, integration, decision speed, and accuracy. Traceability measures the connection among requirements, models, analysis outputs, and validation evidence. Integration measures the connection among tools, datasets, models, and engineering workflows. Decision speed measures how quickly engineering alternatives can be evaluated. Accuracy measures the quality and reliability of system-level decisions.

Each criterion is assigned an equal weight of 0.25 to maintain a balanced comparison. Performance scores are assigned on a 1 to 10 scale based on the expected capability of each scenario. The traditional scenario receives lower scores where fragmented tools, manual interpretation, and limited model continuity reduce performance. The AI-enabled scenario receives higher scores where connected data, model alignment, AI-supported analytics, and lifecycle feedback improve engineering decision support.

The numerical values collected from this comparative assessment are reported in Section 5.1. The graphical comparison of the traditional and AI-enabled scenarios is presented in Section 5.2.

## 5. Results and Discussion

### 5.1 Numerical Results

Table 1 compares the traditional engineering environment and the AI-enabled digital engineering environment across four weighted criteria. The traditional environment achieved a total score of 6.0, while the AI-enabled framework achieved a total score of 8.75. The highest gains are observed in traceability and integration, where the proposed framework connects data, models, analytics, and decisions through a continuous feedback structure. Decision speed and accuracy also improve because AI-supported analytics can assist trade studies, detect patterns, and support validation decisions with stronger data visibility.

Table 1. Evaluation of system performance using weighted multi-criteria decision model.

| Criteria | Weight (w) | Traditional ($x_i$) | AI-Enabled ($x_i$) |
|---|---|---|---|
| Traceability | 0.25 | 6 | 9 |
| Integration | 0.25 | 5 | 9 |
| Decision Speed | 0.25 | 6 | 8 |
| Accuracy | 0.25 | 7 | 9 |
| **Total Score** | **1.0** | **6.0** | **8.75** |

### 5.2 Graphical Results

Figure 2 compares the traditional engineering environment and the AI-enabled digital engineering framework across traceability, integration, decision speed, and accuracy. The AI-enabled framework shows higher scores across all four criteria, with the strongest gains in traceability and integration. These results indicate that connecting data, models, analytics, and decision workflows can improve system visibility, reduce fragmentation, and support more reliable engineering decisions.

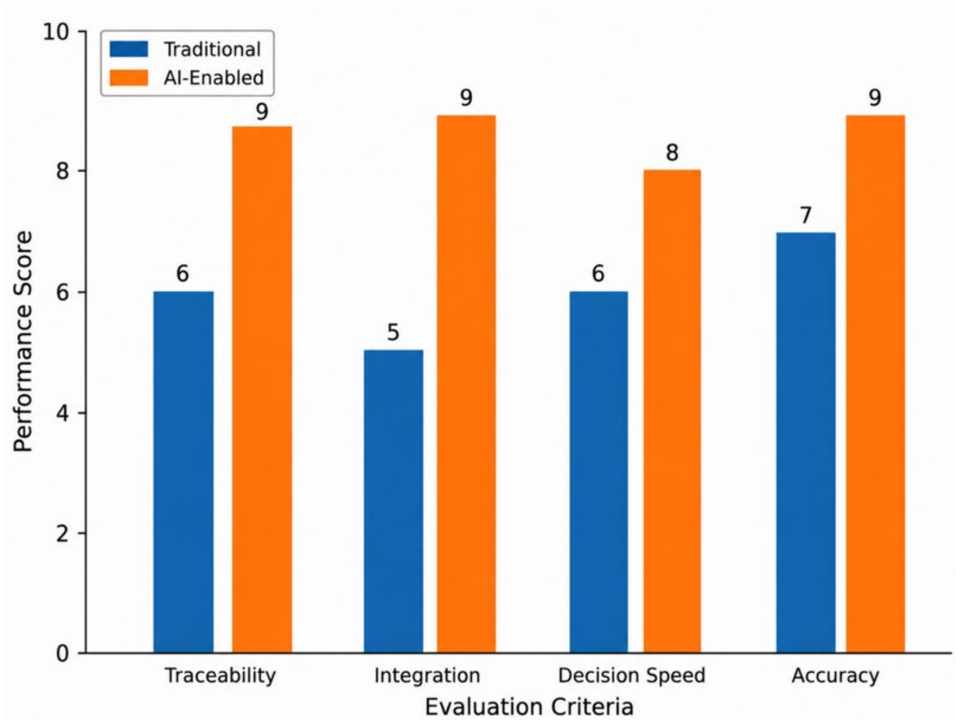


Figure 2. Comparison of evaluation criteria for traditional and AI-enabled digital engineering environments.

### 5.3 Proposed Improvements

The proposed framework improves traditional engineering practice by shifting AI from a separate analysis function into an integrated digital engineering workflow. In practical implementation, organizations should first establish reliable data connections among requirements, models, simulations, and operational records. Next, system models should be linked with AI-supported analytics so that predictions, anomaly detection, and optimization results can be traced back to engineering artifacts. Finally, decision outputs should be connected to trade studies, validation actions, and lifecycle feedback.

These improvements can support better coordination among engineering teams, reduce repeated manual interpretation, and improve visibility across the system lifecycle. For industry practitioners, the framework provides a practical path for using AI in a controlled engineering environment rather than relying on isolated tools. The expected benefit is stronger traceability, faster decision cycles, improved model use, and more reliable system-level decisions.

### 5.4 Validation
The validation in this study is based on a comparative weighted scoring assessment between the traditional engineering environment and the AI-enabled digital engineering framework. The same four criteria and equal weights are applied to both scenarios, which provides a consistent basis for comparison. The traditional environment achieved a score of 6.0, while the AI-enabled framework achieved a score of 8.75. This represents an improvement of approximately 45.8 percent.

$$\text{Improvement (\%)} = (8.75 - 6.0) / 6.0) \times 100 = 45.8\%$$

The validation shows that the proposed framework provides measurable improvement across all selected performance criteria. The result supports the main claim that AI can improve engineering performance when it is connected to data, models, and decision workflows. Since this is a framework-based study, the validation is preliminary and comparative. Future validation should use real project data, industry case studies, and statistical testing across multiple engineering programs.

## 6. Conclusion
This study addressed the need for a structured approach to integrating artificial intelligence within digital engineering environments for complex systems. The paper identified key limitations in traditional engineering practice, including fragmented data, disconnected models, weak traceability, and isolated decision processes. To address these limitations, an industry-oriented AI-enabled digital engineering framework was proposed to connect data integration, model integration, AI-enabled analytics, and decision support across the system lifecycle.

The research objectives were met by developing the framework, defining the evaluation criteria, comparing traditional and AI-enabled engineering scenarios, and demonstrating measurable improvement through a weighted multi-criteria decision model. The results showed that the traditional engineering environment achieved a total score of 6.0, while the AI-enabled framework achieved a total score of 8.75. This represents a 45.8 percent improvement across traceability, integration, decision speed, and accuracy.

The unique contribution of this paper is the integration of AI into the engineering workflow rather than treating AI as a separate analytical tool. By linking AI outputs to requirements, system models, validation evidence, and decision criteria, the proposed framework supports more traceable, consistent, and data-informed engineering decisions. From an industry perspective, the framework provides a practical path for improving lifecycle coordination, reducing manual interpretation, and supporting stronger system-level decisions. Future work should apply the framework to real project data, integrated toolchains, and industry case studies to further validate its scalability and implementation value.

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## Biography

**Iqtiar Md Siddique** is an Assistant Professor in the Department of Manufacturing and Systems Engineering at Weber State University. He received a Ph.D. in Mechanical Engineering and an M.S. in Systems Engineering from The University of Texas at El Paso, an M.Eng. in Computer Engineering from RMIT University, and a B.S. in Computer Science from North South University. His research focuses on systems engineering lifecycle processes, requirements engineering, Model-Based Systems Engineering, digital engineering, aerospace systems, complex adaptive systems, and AI-enabled engineering methods. His doctoral research examined MBSE for aerospace applications, with emphasis on requirements prioritization, lifecycle traceability, digital integration, and small satellite development. Dr. Siddique has served as a Lecturer, INCOSE Academic Equivalency Consultant, Doctoral Research Associate, and Graduate Teaching Assistant at The University of Texas at El Paso. His academic and technical work includes systems modeling, requirements analysis, SysML, Cameo Systems Modeler, MATLAB, STK, Teamcenter, and model-based verification activities. He is a Certified Systems Engineering Professional, SysML Model User, Certified Professional in Requirements Engineering, and Lean Six Sigma Green Belt.