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A Conceptual Digital Engineering Framework for Intelligent and Sustainable Engineering Systems

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ABSTRACT

Digital transformation has reshaped modern engineering by integrating digital technologies that enable data-driven decision-making throughout the engineering system life cycle. This study aims to develop a conceptual digital engineering framework integrating the Internet of Things, Big Data Analytics, Artificial Intelligence, Digital Twin, ontology engineering, and trustworthy artificial intelligence principles to support intelligent, adaptive, and sustainable engineering systems. A qualitative descriptive library research approach was employed by synthesizing scientific publications published over the last five years. The findings indicate that effective digital engineering implementation requires seamless integration among digital technologies, data interoperability, virtual system representation, and transparent, trustworthy decision-making mechanisms. The proposed conceptual framework illustrates the systematic relationship between data acquisition, data management, artificial intelligence-based analytics, Digital Twin representation, and the application of trustworthy artificial intelligence as the foundation of digital transformation. The framework contributes theoretically by strengthening digital engineering as an integrated engineering paradigm while providing practical guidance for organizations in designing digital transformation strategies to improve operational efficiency, system reliability, and long-term sustainability across engineering applications.

Keywords: *Artificial Intelligence, Big Data Analytics, Digital Engineering, Digital Twin, Internet of Things.*

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1. | INTRODUCTION

The development of the Industrial Revolution 4.0 has driven fundamental changes in engineering practices through the integration of digital technologies that enable the design, manufacturing, operation, and maintenance processes to be carried out in a more intelligent, connected, and data-driven manner. This transformation is not only oriented towards process automation, but also emphasizes the ability of engineering systems to process information in real-time, generate accurate predictions, and support adaptive decision-making. Digital engineering is one of the main approaches in realizing this transformation because it is able to integrate the entire system life cycle through the use of interconnected digital models, data, and computing technology (Zimmerman et al., 2019; Huang et al., 2020).

Technological advancements such as Artificial Intelligence (AI), Internet of Things (IoT), Big Data Analytics, Cloud Computing, and Digital Twin have accelerated paradigm shifts in various engineering disciplines. The integration of these various technologies allows engineering systems to no longer operate separately, but to form a digital ecosystem that is able to carry out monitoring, analysis, simulation, and optimization on an ongoing basis. In this context, digital engineering does not only function as a medium for digitizing documents or processes, but develops into an engineering approach that utilizes digital representations to support all engineering activities collaboratively and data-based (Tao et al., 2018; Jones et al., 2020; Liu et al., 2021).

The application of digital engineering is also supported by the development of artificial intelligence methods that are increasingly mature. Machine learning, deep learning, and reinforcement learning have been used to improve the quality of engineering design, predictive maintenance, manufacturing optimization, and the development of decision support systems. Various studies show that the use of AI is able to improve operational efficiency, reduce human error, speed up the analysis process, and improve the system's ability to respond dynamically to changes in operational conditions (Carvalho et al., 2019; Jin et al., 2020; Dworschak et al., 2022). In addition, machine learning techniques are also used in the early stages of engineering, such as identifying user needs and developing system specifications so that the engineering process becomes more adaptive to changing needs (Cheligeer et al., 2022).

On the other hand, the increasingly complex integration of digital technology also presents various new challenges in the implementation of modern engineering systems. Huge data volumes, interoperability between platforms, information security, transparency of artificial intelligence models, and the reliability of digital systems are important issues that need to be considered in the development of data-based engineering. The use of AI without adequate validation mechanisms has the potential to produce decisions that are difficult to explain, biased, or less trustworthy so that they can affect the quality of engineering results. Therefore, the concept of trustworthy AI is an important part of the transformation of digital engineering so that the developed system not only has high performance, but also meets the aspects of transparency, accountability, security, and reliability (Mehrabi et al., 2021; Huang et al., 2021).

In addition to the aspect of artificial intelligence, the development of structured digital representations is also the main foundation in digital engineering. Digital Twin enables a virtual representation of a physical system that can be continuously updated based on actual data, supporting real-time simulation, monitoring, evaluation, and optimization processes. Meanwhile, the development of ontology engineering provides a semantic basis that allows data exchange and interoperability between software and between organizations to be more effective. The combination of these two approaches contributes to improving the quality of decision-making throughout the engineering system lifecycle (Demoly et al., 2019; Driscoll et al., 2021; Liu et al., 2021).

Although various studies have discussed digital engineering from various perspectives, most still focus on the implementation of specific technologies, such as Digital Twins, AI, or IoT separately. Other studies have reviewed applications in specific industry sectors without developing a conceptual framework that integrates all the key components of digital transformation in one comprehensive engineering approach (Huang et al., 2022). This condition shows that there is still a research gap related to how to build a digital engineering framework that is able to integrate digital technology, artificial intelligence, data management, system interoperability, and trust aspects in supporting the development of adaptive and sustainable engineering systems.

Based on these conditions, this study aims to develop a conceptual framework for digital engineering that integrates Digital Twin, Internet of Things, Big Data Analytics, Artificial Intelligence, and trustworthy AI principles into an integrated engineering flow. The proposed framework is expected to make a conceptual contribution to the development of modern engineering systems, become a reference for the implementation of digital transformation in various engineering sectors, and enrich the study of digital engineering as a new paradigm in supporting a smarter, integrated, and sustainable engineering system.

2. | RESEARCH METHOD

This research uses a library research method with a qualitative-descriptive approach to develop a conceptual framework for digital engineering in supporting the implementation of Industry 4.0-based engineering systems. This method was chosen because it allows the synthesis of various results of previous research so that a comprehensive understanding of the development of concepts, technologies, implementation, and research gaps is obtained that is the basis for the preparation of conceptual models.

The research stage begins with the identification of the scope of the study which includes digital engineering, Industry 4.0, Artificial Intelligence, Internet of Things, Big

Data Analytics, Digital Twin, ontology engineering, predictive maintenance, and trustworthy AI. Furthermore, literature searches were carried out through various scientific publications that were at least indexed on Google Scholar by considering the quality, relevance, and year of publication. The references used come from research articles and review articles that discuss digital transformation, intelligent systems, digital manufacturing, and data-based engineering.

The collected literature is then selected and evaluated based on suitability for the research objectives. Each article is analyzed to identify key concepts, methods, outcomes, and development opportunities, then grouped into main themes to facilitate knowledge synthesis. The final stage is carried out through conceptual synthesis by comparing different approaches that have been developed in previous research to identify the relationships between the main components. The results of the synthesis are used as the basis for the preparation of a digital engineering framework that integrates Digital Twin, Internet of Things, Big Data Analytics, Artificial Intelligence, and trustworthy AI principles as a conceptual model that supports decision-making, optimization, and continuous improvement of engineering system performance.

3. | RESULTS AND DISCUSSION

Digital engineering has evolved from simply digitizing documents to an engineering paradigm that integrates data, digital models, artificial intelligence, and computing systems to support the entire life cycle of engineering systems. This paradigm makes digital information the main asset that connects the stages of planning, designing, implementing, operating, evaluating, and improving performance on a sustainable basis. The representation of physical system changes into a digital environment allows analysis and decision-making to be done more quickly, accurately, and evidence-based. This transformation is one of the main characteristics of modern engineering driven by the development of Industry 4.0 (Zimmerman et al., 2019; Huang et al., 2020).

Digital engineering increases efficiency while expanding the system's ability to generate knowledge through the use of data. Unlike conventional approaches that store design, manufacturing, testing, and operations data separately, digital engineering integrates all data sources in one interconnected ecosystem. A continuous flow of information allows every technical decision to be based on actual conditions and predicted results so that engineering systems are created that are more adaptive to changes in the environment and operational needs (Tao et al., 2018; Jones et al., 2020).

One of the main components of digital engineering is Digital Twin as a virtual representation of a physical system that allows real-time data synchronization. Through this approach, simulation, monitoring, diagnosis, and optimization can be carried out without interfering with the actual operation of the system. The implementation of Digital Twin is able to reduce testing costs, accelerate design evaluation, improve the quality of decision-making, and support early identification of potential failures so that operational risks can be minimized (Liu et al., 2021; Rasheed et al., 2020).

The success of the Digital Twin implementation is greatly influenced by the Internet of Things (IoT) which connects sensors, devices, and communication systems. The sensor generates real-time operational data on equipment conditions, process parameters, and the working environment. The data is sent to a digital platform to be processed using analytics and artificial intelligence technology. The integration of IoT and Digital Twin results in a more responsive monitoring system so that system condition evaluation can be carried out on an ongoing basis without relying on manual inspections (Tao et al., 2018; Liu et al., 2021).

The large volume of data generated by IoT puts Big Data Analytics as an important component in digital engineering. This technology processes large amounts of data into valuable information through the identification of operating patterns, relationships between parameters, and system interference tendencies. Thus, data is no longer seen as a by-product, but rather as a strategic source of information that supports decision-making and optimization throughout the life cycle of an engineering system.

Artificial Intelligence (AI) further strengthens digital engineering capabilities through predictive analytics. Machine learning algorithms are able to study historical data to recognize patterns related to system performance, product quality, and potential component failures. The implementation of AI accelerates analysis while improving the accuracy of predictions compared to conventional approaches. In manufacturing, AI is used to optimize production processes, improve additive manufacturing quality, and develop data-driven designs, while reinforcement learning is used to produce optimization strategies that are adaptive to changing operating conditions (Jin et al., 2020; Meng et al., 2020; Dworschak et al., 2022).

Machine learning also contributes to predictive maintenance. Unlike periodic maintenance that follows a fixed schedule, predictive maintenance utilizes sensor data and machine learning algorithms to predict the time of damage so that maintenance actions can be taken before failure occurs. This approach has been proven to reduce system downtime, extend equipment life, and reduce operational costs through the integration of AI, IoT, and data analytics that generate recommendations based on the actual conditions of each component (Carvalho et al., 2019; Black et al., 2021).

In addition to these technologies, ontology engineering plays a role in providing a semantic framework that allows various data, models, and software to understand each other's exchanged information. Interoperability is an important factor because digital engineering involves a variety of applications from different platforms. Ontological modeling allows the relationships between engineering objects to be represented systematically so that data integration becomes more effective and easy to develop according to organizational needs (Demoly et al., 2019; Dimassi et al., 2021).

Digital engineering implementation also requires a trustworthy AI system. The complexity of machine learning and deep learning poses challenges in the form of low transparency, potential algorithm bias, and difficulty explaining the basis for decision-making. Therefore, the concept of trustworthy AI becomes an important foundation by emphasizing the transparency, accountability, reliability, security, and fairness of algorithms. This approach ensures that the system not only produces accurate predictions, but is also able to provide logical explanations that increase user confidence in the results of the analysis (Huang et al., 2021; Mehrabi et al., 2021).

The results of the literature synthesis show that the success of digital transformation can only be achieved through the integration of various technologies. Artificial Intelligence requires quality data from the Internet of Things, Digital Twin requires continuous operational data, Big Data Analytics processes data into AI-ready information, while ontology engineering ensures the interoperability of all components. This relationship shows that digital engineering is a holistic system and cannot be separated into stand-alone components (Jones et al., 2020; Liu et al., 2021; Demoly et al., 2019).

Studies of previous research show that there is still fragmentation in the development of digital engineering. Most research focuses on a single technology, such as Digital Twin, Artificial Intelligence, predictive maintenance, or ontology engineering, without integrating all components in a single conceptual framework. This condition shows that there is a conceptual gap in building a digital engineering model that is able to systematically integrate all digital technologies throughout the life cycle of the engineering system (Huang et al., 2020).

Based on this synthesis, this study proposes a digital engineering framework that starts from data acquisition through the Internet of Things, followed by data integration and management on digital platforms, then analyzed using Big Data Analytics before being utilized by Artificial Intelligence for prediction, classification, optimization, and decision-making. All analysis results are integrated into Digital Twin so that users obtain a real-time virtual representation of the system while supporting simulation of various operational scenarios. At each stage, trustworthy AI principles are applied to ensure transparency, reliability, security, and accountability of analysis results.

The framework has several advantages. Technology integration results in a continuous flow of information so that engineering decisions are based on actual data. Artificial Intelligence is an integral part of the optimization process supported by data quality as a result of the integration of the Internet of Things, Big Data Analytics, and Digital Twin. Ontology engineering strengthens interoperability between software, while the application of trustworthy AI increases confidence in the results of the analysis so that it is suitable as a basis for decision-making in complex engineering environments (Huang et al., 2021; Dimassi et al., 2021; Mehrabi et al., 2021).

Theoretically, this research strengthens digital engineering as an engineering paradigm that integrates data, digital technology, artificial intelligence, and virtual representation in one unified framework. The success of digital transformation is determined not only by technological advancements, but also by information integration, system interoperability, and data governance that support sustainable decision-making. From a practical perspective, this framework can be a reference for organizations in building data-based monitoring systems to improve operational efficiency, reduce the risk of failure, accelerate decision-making, and support predictive maintenance.

However, this research is still limited to a literature study approach so the resulting conceptual framework has not been empirically tested. Further research needs to be validated through case studies, simulations, and implementations in various engineering sectors. Development can also be directed to the integration of edge computing, blockchain for data engineering security, and explainable artificial intelligence to increase the transparency of prediction models. Thus, digital engineering is expected to continue to develop as the main foundation in building an engineering system that is intelligent, integrated, sustainable, and able to answer the challenges of digital transformation in the future.

4. | CONCLUSION

Digital engineering is a modern engineering paradigm that integrates various digital technologies to support the entire life cycle of engineering systems in a more effective, adaptive, and sustainable manner. Based on the results of the literature synthesis, digital transformation in the field of engineering does not only depend on the application of technology individually, but requires a harmonious integration between the Internet of Things, Big Data Analytics, Artificial Intelligence, Digital Twin, ontology engineering, and trustworthy AI principles. The integration allows for the creation of a continuous flow of data, improved analysis quality, optimization of decision-making processes, and the system's ability to monitor and predict in real-time.

This research succeeded in compiling a conceptual framework of digital engineering that describes the relationship between the main components in building a data-based engineering system. The proposed framework places data acquisition as the initial foundation that is then integrated through digital platforms to generate information that can be analyzed using artificial intelligence. The results of the analysis are then represented through Digital Twin as a medium for simulation, evaluation, and optimization, with the application of trustworthy AI principles as a mechanism to maintain transparency, reliability, security, and accountability of every decision produced. This approach provides a more comprehensive picture than previous research which generally still focuses on the implementation of certain technologies separately.

Theoretically, this research strengthens the understanding of digital engineering as a systemic approach that connects people, processes, data, and technology in one integrated digital ecosystem. From a practical perspective, the framework developed can be used as a reference in designing digital transformation strategies in various engineering sectors according to the level of technological maturity that the organization has. In the future, empirical testing of this conceptual framework in various engineering environments is needed to evaluate the effectiveness of its implementation, as well as to refine the model to be more adaptive to the development of digital technology that continues to develop.

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