JOURNAL OF RESEARCH, INNOVATION, AND STRATEGIES FOR EDUCATION
PP. 185-208 (EARLY ACCESS)
https://doi.org/10.70148/rise.v3i5.11

Reframing Engineering Education for the Age of AI-Integrated Digital Twins: A Conceptual Framework for Practice-Oriented Learning

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ABSTRACT
The growing intersection of artificial intelligence (AI) and digital twins (DTs) is transforming the design, operation, and management of engineering infrastructure by enabling data-driven modelling, monitoring, prediction, and decision-making, while integrating engineering processes that have traditionally operated in isolation. However, engineering education has not evolved in parallel with these rapid technological advances, often treating AI and DTs as individual tools rather than inputting them within pedagogical models that promote systems thinking and real-world engineering practice. This gap has created a significant disconnect between conventional engineering education and the evolving competencies required by modern industry. This study proposes a conceptual framework for reframing engineering education through AI-integrated DTs as engineering learning platforms rather than instructional technologies alone. The framework was developed through a structured conceptual synthesis of recent literature, examining the limitations of existing educational approaches and identifying opportunities to strengthen systems thinking, uncertainty management, decision-making, and ethical reasoning within engineering curricula. Based on this synthesis, the proposed framework positions DTs as educational infrastructure that supports continuous student engagement with realistic engineering scenarios. Also, it facilitates practice-oriented learning and strengthens the combination of academic learning with engineering practice and industrial applications. The study contributes a structured theoretical framework to guide curriculum transformation and provides practical implementation pathways for integrating AI-enabled DTs into future engineering education.

ARTICLE HISTORY
Received 28 March 2026
Revised 05 August 2026
Accepted 07 August 2026
Online First 07 August 2026

KEYWORDS
engineering education;
digital twin learning;
artificial intelligence;
practice-oriented learning;
decision-based learning;
curriculum innovation;
industry–academia integration.

CONTACT Abiola Ayopo Abiodun abiola.abiodun@final.edu.tr Department of Civil Engineering, Faculty of Engineering, Final International University, 99370, Catalkoy, Kyrenia, North Cyprus via Mersin 10, Turkey **ISSN : 3030-6582 (Printed), eISSN : 3030-5330 (Online).** DOI 10.70148/rise.v3i5.11. This article Journal of Research, Innovation, and Strategies for Education is available under Creative Commons CC-BY 4.0 license (https://creativecommons.org/licenses/by/4.0). For further queries, please contact Editors at editor@teknologi.edu.my. For further queries, please contact Editors at

1. Introduction

Engineering education is undergoing a significant structural transformation driven by rapid advances in digital technologies and data-intensive engineering practice. This transformation has created a noticeable disconnect between engineering education and professional practice. Interestingly, most engineering professional activities and practices have significantly integrated digital twins (DTs), artificial intelligence (AI), and data-enabled decision systems; on the other, educational structures continue to depend on linear problem-solving models, rigid disciplinary boundaries, and static system frameworks. These divergent approaches have created significant educational imbalances that are becoming increasingly difficult to ignore. In real-world applications, engineers increasingly operate within environments characterised by continuous data flow, data interpretation, predictive modelling, and iterative feedback. By contrast, many engineering classrooms worldwide, learning continues to rely heavily on abstract formulations detached from the appropriate contexts of engineering practice. Consequently, recent studies indicate that this disconnect has widened the gap between how future engineers are educated and the competencies expected in contemporary professional environments (Fuller et al., 2020; Jebelli et al., 2024; Zhang et al., 2025).

At the same time, the role of DTs has evolved considerably. Rather than serving merely as supplementary technological tools, they are increasingly recognized as digital infrastructures through which engineering knowledge is generated, disseminated, tested, and applied (Grieves & Vickers, 2016; Hazrat et al., 2023; Omrany et al., 2026). Despite this growing recognition, their educational integration has progressed more slowly than their industrial adoption. It has been reiterated that in many programs, DTs have appeared only in isolated modules or final-year projects, treated as optional or elective course requirements rather than core components of learning. Existing studies consistently suggest that this fragmented implementation limits the pedagogical value of DTs and reinforces the disconnect between engineering education and professional practice (Karanam, 2025; Daineko et al., 2025).

Alongside discussions on the incorporation of DTs into engineering education, AI is also introducing another dimension to the subject. For instance, in certain engineering domains, AI is now capable of merging optimization processes, risk evaluation, and supporting operational decision-making. As such, students undertaking engineering courses are not only required to interpret AI-generated outputs but also navigate uncertainty and anticipate system behaviour over time within AI-enabled environments (Liu, 2025; Rahman et al., 2026). However, learning models often confine AI to advanced technical instruction, presenting it as a computational subject rather than as an integral component of engineering reasoning and professional judgement. This narrow perspective limits opportunities for students to engage critically with the ethical, analytical, and socio-technical dimensions that increasingly characterise engineering practice (Syarifuddin et al., 2025).

The ongoing discussions in the literature emphasise another direction, namely the importance of practice-oriented and systems-based learning. From this perspective, students are not positioned as passive recipients of theoretical knowledge but rather as active participants engaged in practical engineering problem-solving (Makransky et al., 2021; Ang, 2025). DTs provide a promising platform for supporting this educational transition. Such learning environments enable learners to interact with dynamic system models, evaluate alternative decisions, and experience uncertainty within realistic yet controlled engineering environments (Omrany et al., 2026; Pathak & Upadhyay, 2024). Nevertheless, the literature indicates that a coherent educational framework combining DTs, AI, and practice-oriented pedagogy has yet to be comprehensively developed.

The aim of this study is to address this important gap by proposing a conceptual framework that reframes engineering education through AI-integrated, practice-oriented learning. Rather than treating DTs as independent technological tools, the proposed framework positions them as educational infrastructure capable of supporting learning, assessment, and industry engagement within a unified pedagogical environment. Building upon contemporary research on DTs, AI, and experiential learning, this study integrates curriculum design, instructional practice, and graduate learning outcomes into a logical conceptual model aligned with the growing demands of modern engineering practice. In doing so, the framework responds to increasing international calls for engineering education that prepares graduates to operate effectively within complex, ethical, data-rich, and AI-enabled professional environments.

1.1. Transformation of Engineering Practice in the Digital Twin Era

The nature of engineering practice has become increasingly dynamic, evolving under the influence of DTs, AI, and data-driven engineering approaches. What were once static representations primarily used for design validation or post-development monitoring have evolved into dynamic environments capable of simulating the behavior of physical assets across their entire lifecycle. Thus, DTs integrate sensor information, spatial data streams, and computational models to support analysis, prediction, optimization, and decision-making in infrastructure management, construction operations, and related engineering applications. Recent studies demonstrate that DTs are reshaping engineering practice from static analysis towards continuous, data-informed system management (Fuller et al., 2020; Jebelli et al., 2024; Zhang et al., 2025).

At the centre of this transformation is AI. Rather than serving only a supporting function, AI enhances the capability of DTs to interpret data, recognise complex patterns, and adapt to changing operational conditions. Leveraging machine learning and intelligent data analytics, DTs assist organisations in identifying patterns and evaluating scenarios far beyond traditional analytical approaches. In engineering applications, for instance, DTs enable systems not only in detecting structural deterioration but also in supporting predictive maintenance, performance optimisation, and adaptive responses to changing environmental and operational conditions (Liu, 2025; Liu & David, 2025; Liu, 2025; Syarifuddin et al., 2025). These developments indicate that contemporary engineering practice is transiting from isolated calculations towards continuous interaction with intelligent, data-driven systems.

Despite these advances in professional practice, engineering education has not progressed at the same pace. Conventional education is still largely focused on producing correct answers in simulated environments at the expense of developing professional judgement and adaptive decision-making skills. Although such an approach equips students to undertake well-defined technical tasks, it overlooks the fact that professional engineering environments demand continuous interpretation of uncertain, evolving, and interconnected systems. There is also a notable lack of exposure to DTs, dynamic systems, and AI-enabled engineering tools within many engineering curricula (Álvarez & Hernández, 2026; Kirkwood & Price, 2014). Existing studies consistently suggest that this educational gap is structural rather than incidental, reflecting a persistent mismatch between engineering education and professional practice.

The difference in structure between traditional models of education and modern models of engineering practice is represented schematically in Figure 1. The figure illustrates how the rapid adoption of DTs and AI across industry has significantly outpaced their integration into engineering education, highlighting the need for a corresponding transformation in curriculum design and pedagogical practice.

What this gap actually demonstrates is more than a shortage of technical skills; it reflects a broader misalignment between educational preparation and contemporary engineering practice. While graduates may be able to perform individual technical tasks competently, they often have limited opportunities to develop the integrated reasoning required to interpret data, evaluate complex systems, and make informed decisions under uncertainty. Drawing on the evidence presented, the present study argues that DTs and AI should be repositioned from random segments of the curriculum to foundational elements of engineering education. This reconceptualisation provides the basis for the AI-integrated, practice-oriented educational framework proposed in the subsequent sections.

1.2. Limitations of Traditional Engineering Education Models

Despite the dynamic nature of problem-solving techniques in engineering and technology, the traditional approach to education in the field of engineering has remained largely unchanged. In fact, it continues to be based on a set of assumptions that were valid in a different era, before the widespread integration of digital technologies, AI, and data-driven engineering systems. One of the biggest limitations of the traditional approach to education in the field of engineering is that it continues to be based on a static rather than adaptive curriculum. The primary drawback here is that knowledge is delivered through traditional rather than adaptive instructional approaches. This is often because traditionally, engineering curricula have been organised around well-defined problems with predetermined inputs, processes, and expected outputs, reflecting assumptions that are appropriate for predictable environments but less suited to complex, evolving engineering systems (Kirkwood & Price, 2014; Álvarez et al., 2023). Collectively, these studies suggest that conventional curricula provide limited opportunities for learners to develop adaptive reasoning and systems thinking required in contemporary engineering practice.

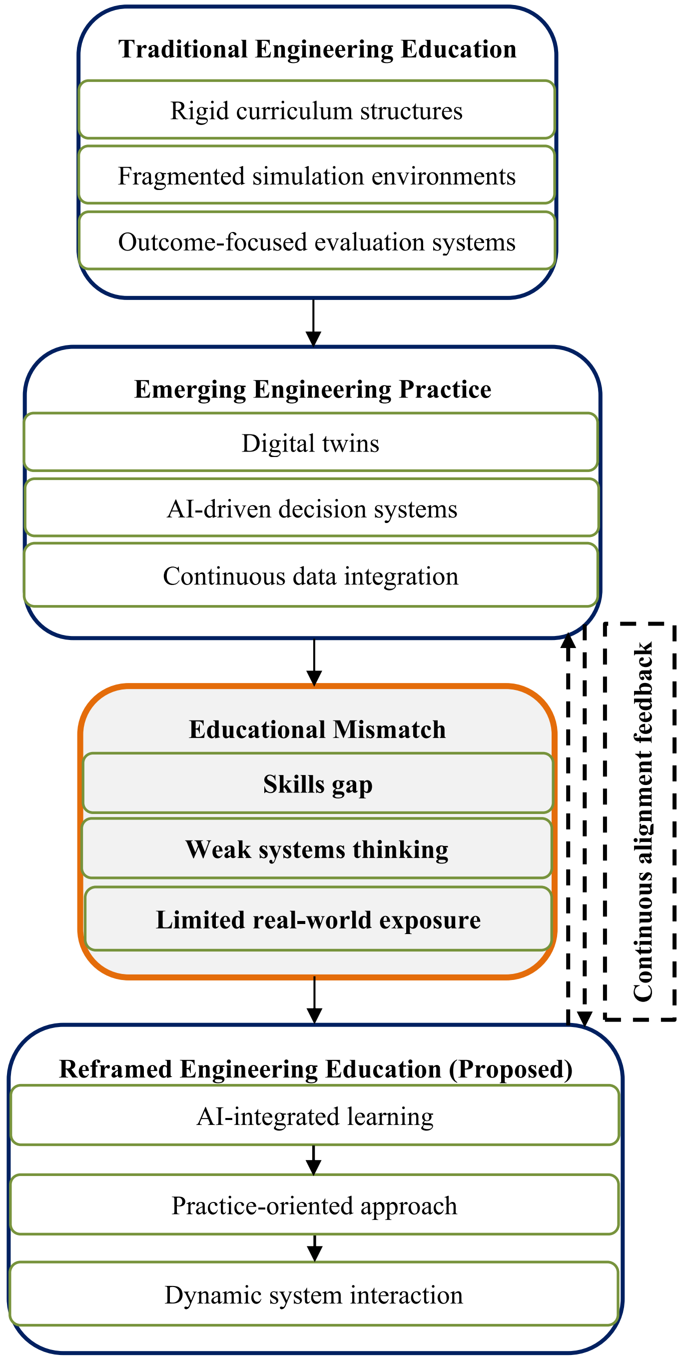

Figure 1. Conceptual Model Illustration of Traditional Engineering Education to AI-Integrated Digital Twin Learning.

Similar limitations exist in conventional engineering simulations. In most cases, the simulations in engineering disciplines are conducted in isolated environments from real-time data, devoid of uncertainty, and limited in terms of time. In most cases, the simulations are conducted as instructional tools, as opposed to decision-making tools. By contrast, real-world DT environments operate continuously, integrating real-time data, uncertainty, and iterative decision-making over extended periods (Tjahyadi et al., 2023; Omrany et al., 2026). This contrast highlights an important pedagogical gap between conventional engineering simulations and the dynamic conditions encountered in professional practice.

Moreover, the methods of assessment also contribute to this disconnection. For instance, conventional assessment emphasises is usually on the accuracy and efficiency of test responses within a given time frame. Conversely, the ability to interpret an incomplete information or to revise one's thinking in light of feedback is not commonly assessed. These competencies are essential because engineering decisions are not always made in a context of certainty; however, such skills are not usually tested (Makransky et al., 2021; Ang, 2025). Existing research therefore indicates a growing mismatch between assessment practices and the competencies increasingly demanded in engineering workplaces, particularly judgement, adaptability, and reflective decision-making.

The most important constraint, on the other hand, might be the handling of complexities. Engineering problems tend to be compartmentalized along disciplinary lines, leaving little room for the exploration of the interplay between technical systems and environmental or human factors. This compartmentalized approach does not allow for the development of the necessary systems thinking, which becomes critical when working with AI-enabled DTs, where data, physical systems, and decision logic come into play. As such, the literature suggests that engineering education should move beyond isolated disciplinary instruction towards integrated learning environments that better reflect the interconnected nature of contemporary engineering systems (Álvarez & Hernández, 2026).

Table 1 summarises the principal differences between traditional engineering education models and the AI-integrated DT approach proposed in this study. The comparison highlights the pedagogical transition from static, examination-oriented instruction towards adaptive, practice-oriented learning supported by continuous interaction, feedback, and authentic decision-making.

Table 1: Educational Transition from Traditional Models to AI-Integrated Digital Twin Learning

Dimension	Traditional Model	Proposed Model
Learning	Fixed and linear	Adaptive and evolving
Assessment	Exams	Performance-based
Feedback	Delayed	Continuous
Practice	Limited	Embedded
Complexity	Simplified	Context-driven and data-informed
Decision-making	Deterministic	Probability and Adaptive

1.3. Educational Opportunity of Digital Twins as Learning Systems

The emergence of DTs offers a new perspective about the nature of engineering education, one that moves beyond their conventional use for the optimization of industrial processes. In reality, DTs represent dynamic digital representations of physical objects, where sensor data, computer models, and predictive modelling converge. Recent studies increasingly recognise that these characteristics also provide important educational opportunities by enabling authentic, data-rich learning environments that closely resemble professional engineering practice. In the classroom, this same architecture can be repurposed for learning, where students can be presented with systems that vary over time, respond to input, and mimic the kinds of ambiguity and interdependence found in the real world. (Karanam, 2025; Omrany et al., 2026; Daineko et al., 2025).

What is enabled in such environments is not just interaction, but sustained engagement. Decisions are not just singular actions, but processes. A parameter is not adjusted or a system condition changed in isolation. Instead, the consequences of such actions propagate throughout the system. Sometimes, the response is immediate; sometimes, it is not. The student must then analyze the response and refine their strategy. The focus is not so much on quickly obtaining correct solutions, as it is in understanding the behavior of the system as conditions change. This processoriented form of learning promotes more fundamental conceptual understandings, particularly when such concepts are continually challenged by the system's response (Pathak & Upadhyay, 2024). Consistent with experiential learning theory, this continuous interaction encourages learners to develop engineering judgement through iterative observation, reflection, and informed decision-making rather than through memorisation alone.

AI introduces an additional pedagogical dimension with the inclusion of AI. This allows the DT to move from passive representation to active engagement. This means that it is possible to have variation, scenarios that respond to user inputs, and feedback in real time. The patterns, anomalies, and trade-offs that are often opaque to the novice learner are clarified through more visible data-driven inference. In this way, it becomes possible to see AI not just as a background tool but as an educational mediator linking theory, data, and decision-making in ways that support practical understanding within the context of engineering education (Syarifuddin et al., 2025; Kotecha et al., 2025). Collectively, these studies suggest that AI strengthens the pedagogical value of DTs by supporting adaptive learning, personalised feedback, and transparent reasoning processes.

Most notably, these environments represent a beginning attempt to develop forms of judgment and thinking that are difficult to achieve through other means. Students are presented with environments in which goals are at odds, information is lacking, and outcomes are unpredictable. Decisions need to be justified as well as calculated. As such, these AI-driven DTs are not simply tools for instruction; they represent a space between academic and professional practice. Based on the educational opportunities identified in the existing literature, the present study proposes that DTs should be reconceptualised as educational infrastructure capable of integrating learning, assessment, and industry engagement within a unified AI-supported environment. Redefining these DTs as educational infrastructure, as opposed to technological tools, is a means of beginning to align engineering education with the needs of contemporary practice.

1.4. Aim, Scope, and Conceptual Contribution of the Study

This study recognises that contemporary engineering education is increasingly misaligned with the realities of modern engineering practice. The primary objective of this study is to reconsider the model of learning in the context of AI-integrated DTs. Unlike conventional approaches, where DTs and AI are often introduced as advanced or supplementary technologies, this study positions them as foundational educational infrastructure capable of transforming how engineering knowledge is acquired, applied, and assessed. The aim is not to advance technological development, but to address the pedagogical imbalance, in which data-driven, decision-based engineering practice continues to be modeled using static, content-based models (Álvarez & Hernández, 2026; Rahman et al., 2026). Drawing on the educational gaps identified in the preceding sections, the proposed framework seeks to realign engineering education with the evolving demands of AI-enabled professional practice.

The scope of the work is conceptual in nature and aims to bring together literature from engineering education, DT technologies, AI, and experiential learning. Based on the literature, the study develops a unified framework that integrates curriculum development, learning processes, and assessment practices. Rather than focusing on a single engineering discipline, the framework is intended to provide transferable educational principles applicable across civil, mechanical, electrical, and related engineering programmes at both undergraduate and postgraduate levels. The framework is designed to highlight aspects of learning that reflect real-life engineering practices, including continuous interaction with systems, uncertainty, ethics, and reflective decision-making (Karanam, 2025; Omrany et al., 2026).

The uniqueness of this conceptual article lies in the shift in perspective on the concept of DTs. DTs are not viewed only as industrial tools but also, and more importantly, as educational infrastructure that supports learning, assessment, and professional engagement. Consistent with recent literature recognising the educational potential of AI-enabled learning environments, the inclusion of AI-enhanced DTs creates an integrated environment that connects theory, simulation, practice, and assessment within a coherent pedagogical framework. In doing so, the proposed framework extends existing educational approaches by integrating technological innovation with practice-oriented learning rather than treating these elements as separate curriculum components (Syarifuddin et al., 2025; Pathak & Upadhyay, 2024).

The importance of this contribution extends beyond individual institutions and regions. As engineering practice continues to evolve through digital transformation, educational institutions face increasing pressure to prepare graduates for data-intensive, AI-supported professional environments. Accordingly, the proposed framework offers adaptable pedagogical principles rather than technology-specific solutions, allowing its application across diverse institutional and geographical contexts. By integrating DTs, AI, experiential learning, and curriculum design within a unified conceptual model, this study contributes to ongoing international efforts to strengthen engineering education for Industry 4.0 and future intelligent engineering ecosystems (Álvarez et al., 2023; Daineko et al., 2025).

2. Methodology

2.1 Research Design

This study adopts a conceptual framework research design supported by a structured literature synthesis to examine how engineering education can be reframed for the era of AI-integrated DTs. Rather than generating empirical evidence through experimentation or field investigation, the study draws upon existing literature to analyse, organise, and integrate contemporary perspectives into a coherent educational framework. Such an approach is appropriate when the objective is to advance theory, clarify emerging concepts, and propose new directions for educational practice in rapidly evolving fields (Jaakkola, 2020).

A conceptual research design was selected because the intersection of DTs, AI-enabled learning, and engineering pedagogy remains fragmented across multiple disciplines. Existing studies frequently examine these themes independently, for example, DTs in engineering practice, AI in education, or experiential learning, while relatively few attempts to integrate them within a unified pedagogical perspective. Consequently, a structured conceptual synthesis provides an appropriate means of identifying relationships among these bodies of knowledge and developing a framework capable of informing curriculum innovation and future educational research (Snyder, 2019; Paul & Criado, 2020).

The study therefore follows an interpretive and integrative approach to knowledge development. Relevant literature was systematically identified, critically evaluated, and synthesised to reveal recurring concepts, complementary perspectives, and unresolved gaps. Rather than summarising previous publications, emphasis was placed on comparing viewpoints, identifying conceptual convergence, and constructing a logically connected framework grounded in current literature. This process supports the development of an educational model that is theoretically informed, pedagogically relevant, and applicable across diverse engineering education contexts.

The methodological strategy adopted in this study is designed to maximise transparency and reproducibility. Explicit procedures for literature identification, study selection, conceptual analysis, and framework development are presented in the following subsections. Although conceptual studies do not seek statistical generalisation, methodological rigour can be strengthened through systematic documentation of the review process, clear analytical procedures, and traceable links between published evidence and the resulting conceptual propositions (Booth et al., 2021; Torraco, 2016). These principles guided the development of the proposed framework throughout the study.

2.2 Literature Search Strategy

A structured literature search was conducted to identify studies relevant to engineering education, digital twins (DTs), artificial intelligence (AI), and practice-oriented learning. The search aimed to ensure broad disciplinary coverage while maintaining a focused alignment with the development of the proposed conceptual framework. Literature was sourced from major academic databases and publishers, including Scopus and Web of Science, as well as IEEE Xplore, ScienceDirect, SpringerLink, Taylor and Francis, Wiley, and MDPI, which collectively provide extensive coverage of engineering, education, and information technology research.

Search terms were developed iteratively by combining keywords and Boolean operators, including engineering education, DTs, AI, AI-integrated learning, practice-oriented learning, experiential learning, curriculum innovation, and industry–academia collaboration. To ensure that the framework reflected contemporary developments, priority was given majorly to publications published between 2020 and 2026, while earlier key methodological studies were included when relevant.

The literature search followed a staged screening process. Titles and abstracts were first reviewed to determine relevance to the research objectives, after which potentially eligible studies underwent full-text assessment. Additional publications were identified through multiple citation tracking of influential articles. The structured search strategy and conceptual synthesis approach adopted in this study were informed by established guidance on conceptual and literature-based research (Booth et al., 2021; Jaakkola, 2020; Paul & Criado, 2020; Snyder, 2019). Table 2 summarises the major literature resources, search strategy, eligibility criteria, and analytical procedures adopted to ensure a transparent and systematic conceptual synthesis.

Table 2: Literature Resources and Selection Strategy Used for the Conceptual Framework Development

Methodological Component	Description
Research design	Conceptual framework development supported by a structured literature synthesis.
Purpose of the review	To synthesise current knowledge on engineering education, DTs, AI, and practice-oriented learning to develop an integrated educational framework.
Databases searched	Elsevier, MDPI, Web of Science, ScienceDirect, Scopus, SpringerLink, Taylor and Francis, and Wiley.
Publication period	Primarily 2020–2026; seminal methodological studies were included where directly relevant to conceptual framework development.
Search keywords	Engineering education, DTs, AI, AI-integrated learning, practice-oriented learning, experiential learning, curriculum innovation, and industry–academia collaboration.
Search strategy	Keywords were combined using Boolean operators (and/or) and adapted to the indexing structure of each database to maximise retrieval of relevant publications.
Eligible sources	Peer-reviewed journal articles, review papers, high-quality conference proceedings, and recognised methodological references.
Exclusion criteria	Publications unrelated to engineering education, studies lacking conceptual relevance, duplicate records, editorials, opinion papers, non-peer-reviewed web sources, and publications with insufficient methodological transparency.
Screening procedure	Sequential screening of titles, abstracts, and full texts, followed by backward and forward citation tracking to identify additional relevant studies.
Analysis approach	Iterative thematic comparison and conceptual synthesis to identify recurring concepts, educational gaps, and relationships that informed framework development.
Outcome	Development of a conceptual framework that integrates AI-enabled DTs with practice-oriented engineering education through evidence-informed synthesis.

2.3 Inclusion and Exclusion Criteria

To ensure that the conceptual framework was developed from relevant and high-quality sources, explicit inclusion and exclusion criteria were applied throughout the literature selection process. Studies were considered eligible if they examined one or more of the following themes: engineering education, DTs, AI in educational or engineering contexts, practice-oriented learning, experiential learning, curriculum innovation, or industry–academia collaboration. Preference was given to peer-reviewed journal articles because they provide greater methodological scrutiny and research reliability.

Publications were excluded when they focused exclusively on technical implementation without educational relevance, lacked sufficient methodological or theoretical detail, or duplicated findings already represented in the selected literature. Editorials, opinion pieces, non-scholarly web sources, and unpublished manuscripts were also excluded unless they constituted recognised methodological references that supported the conceptual approach adopted in this study.

Applying these criteria improved the consistency of the literature selection process and ensured that the proposed framework was informed by credible, relevant, and educationally meaningful evidence. The criteria also reduced the likelihood of incorporating peripheral studies that did not contribute directly to the study's aim of reframing engineering education through AI-integrated DTs (Snyder, 2019; Paul & Criado, 2020; Booth et al., 2021).

Table 3: Summary of Literature Resources Included in the Conceptual Synthesis

Literature Category	Purpose
Engineering education	Pedagogical foundations
Digital twins	Learning environments
Artificial intelligence	Adaptive learning
Experiential learning	Practice-oriented pedagogy
Curriculum innovation	Educational implementation
Industry–academia collaboration	Professional alignment

2.4 Literature Analysis and Conceptual Synthesis

The selected literature was analysed through an iterative process of conceptual comparison and thematic synthesis. Rather than treating each publication independently, the review focused on identifying recurring concepts, complementary perspectives, and areas of divergence across the literature. This analytical approach enabled the integration of knowledge from engineering education, DTs, AI, and practice-oriented learning into a unified conceptual perspective (Jaakkola, 2020; Snyder, 2019).

The analysis progressed through four interconnected stages. First, the included studies were examined to identify their primary educational concepts, theoretical foundations, and reported contributions. Second, similar concepts were grouped into broader thematic categories, allowing relationships between previously isolated research areas to emerge. Third, the resulting themes were critically compared to identify conceptual integration, unresolved inconsistencies, and gaps within the existing body of knowledge. Finally, these findings were synthesised to develop the proposed educational framework, ensuring that each component was explicitly grounded in the reviewed literature rather than inferred from a single source.

Throughout the synthesis, emphasis was placed on interpretation rather than aggregation. The objective was not to determine the frequency with which particular concepts appeared, but to understand how existing knowledge could be reorganised into a coherent framework capable of explaining the educational role of AI-integrated DTs. This interpretive process strengthened the theoretical coherence of the framework while preserving traceable links between the proposed model and the supporting literature (Paul & Criado, 2020; Booth et al., 2021). The workflow illustrated in Figure 2 was developed to provide a transparent representation of the literature identification, screening, analysis, and conceptual synthesis procedures adopted in this study, drawing on established guidance for conceptual and structured literature reviews (Snyder, 2019; Jaakkola, 2020; Booth et al., 2021).

2.5 Methodological Rigour and Conceptual Credibility

Methodological rigour was maintained throughout the study by adopting a transparent and systematic conceptual synthesis process. Each stage from literature identification and study selection to thematic analysis and framework development, followed predefined procedures designed to ensure consistency and traceability. Documenting these procedures improves the reproducibility of the review and allows readers to understand how the proposed framework was derived from the underlying body of literature rather than from subjective interpretation alone (Booth et al., 2021; Snyder, 2019).

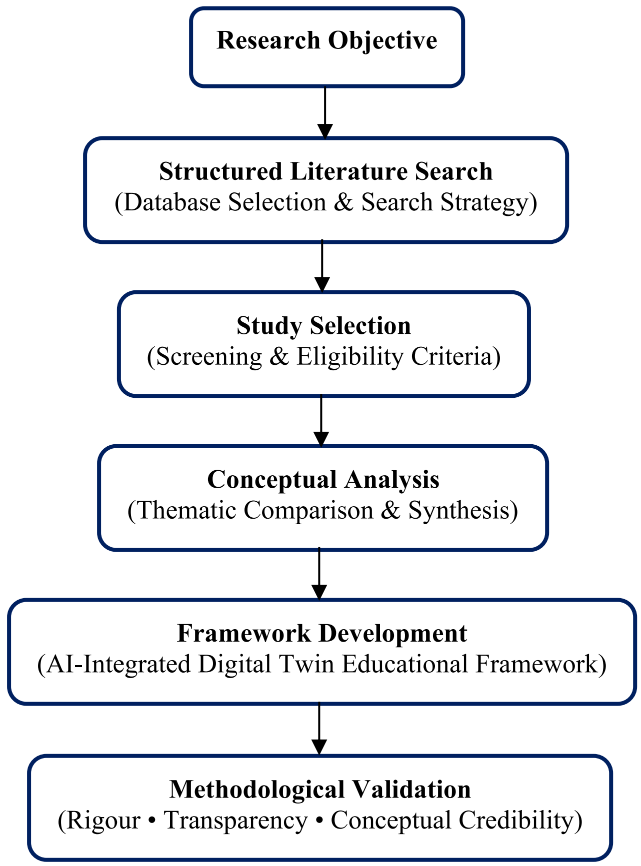

Figure 2. Methodological Workflow for Literature Search and Conceptual Framework Development

The conceptual credibility of the framework was strengthened through the integration of evidence drawn from multiple disciplinary perspectives, including engineering education, DT technologies, AI, experiential learning, and curriculum innovation. Rather than relying on isolated publications, the framework emerged from recurring concepts and convergent findings identified across the selected literature. This triangulation of scholarly perspectives reduced conceptual bias and supported the development of a coherent educational model grounded in current knowledge (Jaakkola, 2020; Paul & Criado, 2020).

Transparency was further improved by explicitly reporting the literature search strategy, eligibility criteria, analytical procedures, and synthesis process. These methodological decisions provide an auditable trail linking the reviewed evidence to the proposed conceptual framework. Collectively, these measures strengthen the methodological integrity of the study and improve its credibility, transferability, and usefulness for future research and curriculum development within engineering education. Together, Table 2 and Figure 2 provide a transparent summary of the methodological procedures adopted in this study. They were developed specifically to document the literature identification, conceptual synthesis, and framework development processes in accordance with established principles of conceptual research and structured literature synthesis (Jaakkola, 2020; Snyder, 2019; Paul & Criado, 2020; Booth et al., 2021).

3. Conceptual and Theoretical Foundations

3.1. Digital Twins Beyond Industry Use

DTs have been traditionally defined and applied as industrial tools for design optimization, monitoring, and control. Initial applications of DTs have concentrated on improving efficiency, minimizing downtime, and promoting predictive maintenance through the synchronization of physical assets and DTs. Early studies consistently describe DTs as virtual representations of physical assets that enable continuous data exchange and informed decision-making across engineering systems (Grieves & Vickers, 2016; Fuller et al., 2020). Although these applications have demonstrated significant operational and economic benefits, their primary emphasis has remained on industrial efficiency rather than on educational innovation.

Despite the recent literature, it has also been demonstrated that there has been a shift in the concept of DTs. Recent literature suggests that the role of DTs is evolving beyond their traditional industrial functions. In other words, DTs are no longer considered a tool for decision-making or a tool for application within a specific domain of professional activity but are considered a tool for creating a cognitive system that is able to learn and interact. Data integration tools and sensors, along with advances in AI tools, have made it possible for DTs to shift from a tool for application within a specific domain of professional activity to a tool for creating a dynamic environment that is able to represent behavioral patterns and responses (Liu & David, 2025; Zhang et al., 2025). Primarily, these developments indicate that DTs can no longer be viewed solely as engineering tools; they also possess characteristics that support interactive learning and informed decision-making. Such a transition also offers opportunities for application within the pedagogical sphere, particularly for the unique case of engineering studies where system dynamics play a major role. Despite this shift, relatively few studies have examined how these capabilities can be systematically incorporated into engineering education, leaving an important pedagogical gap.

From an educational point of view, the unique feature of DTs is their persistency and reactivity. In other words, DTs are long-lived systems that are able to respond to changes in data and interactions with users. Such a feature of DTs offers the student the opportunity to experiment with cause-effect relationships over long timescales and see how local changes impact global system behavior. Unlike static instructional tools, DTs allow learners to observe how engineering systems evolve over time, evaluate the consequences of their decisions, and explore interactions between multiple system variables. Studies show that such persistency aids learning by providing a context where abstract concepts are embedded into a physical system (Omrany et al., 2026; Karanam, 2025). These findings reinforce the educational potential of DTs while highlighting the need for learning environments that reflect the complexity of real-world engineering practice.

In addition to this, it must also be recognized that DTs have educational affordances that extend beyond visualization. As a learning system, it has the potential to function as an environment for hypothesis testing and analysis. The student does not simply play the role of a passive observer but rather as an active participant whose choices affect the system. Makransky et al. (2021) and Pathak and Upadhyay (2024) similarly argue that immersive and experiential learning environments promote active knowledge construction by encouraging learners to test assumptions, evaluate alternatives, and reflect on decision outcomes. Building upon these perspectives, DTs may be reconceptualised as educational platforms where students actively engage with uncertainty, analyse system behaviour, and develop higher-order problem-solving skills rather than merely observing engineering processes.

The literature also indicates that the reframing of DTs as pedagogical systems necessitates a deliberate change of intent in their design. Educational DTs need to be designed to reveal uncertainty, trade-offs, and limits as opposed to hiding these through optimized outcomes. This perspective extends beyond technical proficiency by positioning DTs as environments where learners develop engineering judgement, critical reflection, and responsible decision-making under realistic conditions. These reframing of DTs as platforms for learning judgment and responsibility, as opposed to technical proficiency, offers engineering education the opportunity to extend the scope of DTs to leverage these as foundational infrastructure for the development of the analytical and reflective skills required of contemporary engineering practice.

Overall, the existing literature demonstrates a gradual transition from viewing DTs as operational technologies to recognising their broader educational potential. Nevertheless, current research remains fragmented, with limited integration of DTs, AI, and practice-oriented pedagogy within a single educational framework. The present study addresses this gap by proposing a conceptual model that repositions AI-integrated DTs as educational infrastructure capable of supporting learning, assessment, and industry–academia engagement within contemporary engineering education.

3.2. Artificial Intelligence in Engineering Learning Contexts

AI is increasingly recognised as a key enabler of contemporary engineering education because of its ability to support adaptive learning, intelligent feedback, and data-informed decision-making. Recent studies suggest that AI complements DTs by transforming them from static digital representations into intelligent learning environments capable of responding to learner interactions and changing system conditions (Luckin et al., 2016; Zawacki-Richter et al., 2019).

For a long time now, the concept of DTs has been discussed and defined in terms of an industrial logic. The development and application of DTs have been linked to the need to optimize certain processes and improve the efficiency of systems and their operation. In the early days of their application, the emphasis was on the connection of physical objects to their virtual counterparts to prevent downtime and plan for predictive maintenance. In this sense, the application of DTs is instrumental and is geared towards the performance of the organization and the economy at large, without considering their possible application and role in the field of education (Grieves & Vickers, 2016; Fuller et al., 2020).

This perspective, however, is now beginning to alter. More recent studies do not view DTs as being static or being narrowly defined around decision support tools. Rather, DTs are always considered systems that are constantly evolving and are able to interact, adapt, and to a certain extent, even learn. Such a perspective is also closely related to advances made in sensors, data integration, and AI that enable DTs to not only represent the system but also its behavior under changing conditions. Such elements of uncertainty, variation, and time are now embedded within the system (Liu & David, 2025; Zhang et al., 2025; Kotecha et al., 2025), making them particularly relevant to domains where system behavior is as significant as system structure. Collectively, these studies demonstrate that AI extends the educational potential of DTs by enabling more adaptive, interactive, and context-aware learning experiences.

From a perspective of learning, the defining feature of DTs is not just their technological complexity, but their behavior over time. In contrast to static and simplistic digital teaching simulations, DTs is sustainable and adaptive in nature. This means they not only evolve over time in response to new information, but also in response to the actions of users. This changes the nature of the engagement. This allows students to track the progression of decisions and the effects of decisions. This makes the principles more relevant to the processes in which they operate, as they can be observed and reviewed (Omrany et al., 2026; Karanam, 2025). Previous studies further indicate that AI-supported learning environments improve students' ability to interpret engineering data, evaluate alternative solutions, and understand complex system behaviour beyond isolated learning activities.

The importance of this extends beyond the level of representation. In the form of an educational environment, the DT provides the opportunity for exploration, which extends beyond the level of observation. In this regard, it is possible to explore assumptions, weigh up alternatives, and reflect on the consequences, which may or may not be predictable. The nature of the learner's engagement also varies. Rather than the learner being the passive recipient of information, the learner has the opportunity to influence the nature of the system's response through their decisions. This form of engagement echoes the experiential or constructivist approach to learning, whereby knowledge is constructed through the learner's interaction (Makransky et al., 2021; Pathak & Upadhyay, 2024). Building on these perspectives, AI strengthens this interaction by supporting continuous feedback, adaptive guidance, and reflective decision-making throughout the learning process.

However, the repositioning of DTs is not necessarily straightforward. In the case of DTs as pedagogical systems, complexity needs to be revealed rather than hidden. This means there is a need to ensure the visibility of uncertainty, the visibility of trade-offs, and the visibility of the limitations of the system. Similarly, the educational integration of AI requires transparency, explainability, and responsible decision-making to ensure that learners understand not only engineering outcomes but also the reasoning behind AI-supported recommendations. In such contexts, the notion of execution is not necessarily limited to judgment and responsibility. Although recent studies recognise the educational potential of AI-enabled DTs, relatively few have integrated AI, DTs, and practice-oriented pedagogy within a unified conceptual framework. The present study addresses this gap by positioning AI as an enabling component of DT learning environments that support engineering judgement, authentic assessment, and stronger industry–academia alignment.

3.3. Practice-Oriented and Experiential Learning Theories

Rethinking engineering education within the context of the present day is not simply a matter of making adjustments; rather, it is a matter of fundamentally shifting the way in which the concept of learning is thought of. Practice-based and experiential learning theories are good starting points, and these are largely applicable within contexts of uncertainty and complexity in real-time decision making. Such theories of learning are shifting the focus of education from a form of knowledge transfer to a form of knowledge engagement; and within the context of engineering education, this is highly applicable to the real world of practice, in terms of interpreting system conditions and making decisions in imperfect information contexts (Makransky et al., 2021; Kirkwood & Price, 2014). Collectively, these perspectives emphasise that engineering competence is developed not only through acquiring technical knowledge but also through active engagement with authentic engineering problems and reflective decision-making.

Experiential Learning Theory is one of the most well-recognized frameworks for such a shift. Described as the process of experience, reflection, conception, and experimentation, the emphasis is placed on the importance of ‘‘learning by doing.’’ In the context of engineering education, the importance of such a shift is highlighted in the context of the student being exposed to problem scenarios where there is not a straightforward solution, rather judgment and accommodation must be exercised. Research has indicated the importance of such a scenario in the development of a deeper understanding of the material as the student is able to interact with the systems in a way that reacts dynamically to their decisions (Makransky & Petersen, 2019; Pathak & Upadhyay, 2024). Building on these findings, experiential learning provides an appropriate pedagogical foundation for AI-enabled DT environments, where students continuously test assumptions, evaluate outcomes, and refine their understanding through iterative interaction.

A similar perspective also arises through the concept of situated cognition. This concept focuses on the fact that knowledge cannot be separated from the context in which it is being used. Learning, therefore, occurs in a way that it is influenced by the tools and environment of the context. Learning of engineering competencies occurs in a more efficient way if the environment reflects the context of the real world, in which data and tools are being used rather than being abstracted (Álvarez et al., 2023; Daineko et al., 2025). These studies reinforce the view that authentic learning environments strengthen students' ability to transfer theoretical knowledge into professional engineering practice. This poses an important question of the continued use of isolated simulations and exercises that do not reflect the interconnected nature of systems.

Constructivist theories take this idea one step further by emphasizing the ways in which the learner seeks meaning. Rather than accepting knowledge as a passive recipient, the learner is seen as one who seeks meaning through interpretation, testing, and revision. Research suggests that when the learner is placed in a context that forces them to address the unexpected, their ability to think systemically is enhanced. Such a context also offers the opportunity for ethical thinking, especially when the outcome is visible and unintended (Syarifuddin et al., 2025; Kotecha et al., 2025). Across these studies, constructivist and experiential perspectives suggest that meaningful engineering learning emerges through interaction, reflection, and informed decision-making rather than through passive knowledge acquisition alone.

However, despite the strength of these theoretical foundations, the application of such approaches in the engineering curriculum is not consistently strong. Experiential learning is not necessarily integrated throughout the curriculum in the way these pedagogical theories advocate, but rather in isolated moments such as capstone projects or industrial internships (**Álvarez & Hernández, 2026**; **Ang, 2025**). Consequently, students often experience a disconnect between theoretical instruction and authentic engineering practice. What is needed is a continuous learning environment where theory, simulation, decision-making, and reflection are integrated throughout the educational process. Highlighting the theoretical perspectives discussed above, the present study proposes AI-integrated DTs as a conceptual platform capable of supporting this form of sustained practice-oriented learning within engineering education.

3.4. Gaps in Existing Educational Frameworks

Although interest has been shown in AI and DTs within engineering education, their integration is not uniform. Rather, it has been observed that, in most cases, these components are integrated as separate innovations, rather than being integrated within each other. It has been observed that AI, DTs, and pedagogy are not integrated with each other; rather, they are integrated separately, which has led to fragmentation, instead of their integration being of mutual benefits to support the skills needed within complex data-driven engineering contexts. Existing studies consistently indicate that AI, DTs, and pedagogical practice have largely evolved along separate research pathways, resulting in fragmented educational approaches rather than cohesive learning ecosystems capable of supporting complex, data-driven engineering practice (Álvarez et al., 2023; Daineko et al., 2025). Consequently, learners are often exposed to these technologies independently instead of experiencing their complementary educational value.

Another obvious gap arises with the way in which curriculum content engages with application. DTs are often used as examples of the latest and greatest in simulation tools. However, their application is often limited to specific sections of the curriculum (Tjahyadi et al., 2023; Omrany et al., 2026). In other words, it is rare that DTs are used across the entire curriculum as a continuous environment focused on the student. This allows students to interact with the technology but does not necessarily provide them with a deeper understanding of the overall process. The available evidence suggests that DTs are frequently introduced as isolated instructional technologies rather than as continuous educational environments capable of supporting progressive learning throughout an engineering programme.

A similar pattern can be seen in the use of AI. While AI is increasingly present in the educational sphere, the focus is not always placed on the potential of AI as a means of enhancing thinking and reflection. There is a sense in which many AI-based applications occur behind the scenes, with little in the way of transparency. As such, there is less potential for students to think critically about aspects such as bias and the potential for AI (Liu, 2025; Syarifuddin et al., 2025). This suggests that AI is often employed to automate educational processes rather than to actively cultivate students' critical reasoning, ethical awareness, and reflective engineering judgement.

The process of assessment also creates additional complexity in the picture. For instance, while many engineering programs emphasize experiential or practice-based education, the methods of assessment used in these programs are not always innovative. For instance, timed tests and static problem sets remain the norm, valuing speed and accuracy over judgment and flexibility (Rahman et al., 2026; Ang, 2025). Such methods are not well-equipped to measure skills that are dynamic over time, or to assess judgment or the ability to respond to changing conditions. Without such methods of assessment, efforts to innovate engineering education may be superficial at best. Previous studies therefore highlight a growing mismatch between contemporary learning approaches and conventional assessment practices, limiting the evaluation of higher-order engineering competencies.

There is also a broader issue of a lack of cohesive structures that bridge the gap between curriculum and industry engagement. Therefore, while there is a general encouragement of the collaboration between industry and academia, it is not integrated into the day-to-day running of teaching. In the view of Grieves & Vickers, 2016 and Kotecha et al., 2025, there is a disconnect between the student and the "industry" that is only felt during specific instances of their learning journey, such as during an internship or thesis. This disconnects learning from work practices (Grieves & Vickers, 2016; Omrany et al., 2026). These findings indicate that industry engagement remains episodic rather than systematically embedded within engineering curricula, reducing opportunities for students to connect classroom learning with authentic professional practice.

Conclusively, these limitations highlight the need for a more integrated approach. Indeed, addressing the problems of fragmentation, misalignment, and weak connections between theory and practice cannot be accomplished by making a series of conventional changes. What is called for is a framework wherein AI and DTs are featured as core pedagogical infrastructures that not only influence what is being learned but also how learning is being conducted and how it is being assessed. Building upon the collective evidence presented above, the proposed framework responds directly to these limitations by integrating AI, DTs, practice-oriented pedagogy, assessment, and industry engagement within a unified educational model. In the section that follows, this conceptual framework is presented as a means of aligning engineering education more closely with the evolving demands of contemporary frameworks.

4. Proposed Educational Framework

4.1. Reframing Digital Twins as Educational Infrastructure

In the context of this research, it was recognized that DTs are not seen as additional tools added to existing pedagogic approaches. Instead, the role of DTs was seen to be more fundamentally reconsidered. Rather than being seen as merely digital representations of physical assets, it was examined that DTs are fundamental systems of education. Extending the literature synthesised in Section 3, the present study reconceptualises DTs as educational infrastructure that supports continuous learning rather than isolated technological interventions. This results in a perspective that is not tool-related but environment-related, in which interaction with engineering systems is seen as continuous rather than episodic.

From the perspective of the theory of learning, this suggests a different form of exposure. The students are not limited to specific forms of scenarios and data. They are exposed to the systems. The conditions are constantly changing. The results do not always follow a specific pattern. In such a scenario, knowledge is developed over time. This knowledge is often developed by revisiting the existing knowledge. The choices have a lasting impact. They affect the state of the system over time and scale. In such a scenario of interaction, specific forms of reasoning are developed. This reasoning goes beyond computation. It enters the domain of interpretation, anticipation, and awareness. (Omrany et al., 2026; Karanam, 2025; Daineko et al., 2025). These characteristics are consistent with experiential and constructivist learning theories, which emphasise continuous interaction, reflection, and contextual understanding as essential elements of meaningful engineering education.

The concept of assessment also assumes a different dimension. Instead of assessing the correct answer and solution, it becomes linked with the student's approach to dealing with complexity. The activities undertaken in the system, modifications, responses, and approaches are also traceable and assessable over a specific period of time. The answer and solution are no longer of primary concern. The concern now becomes the approach to obtaining the answer and solution. The approach and solution are linked with the results obtained. In a way, it becomes a reflection of competence rather than a presumption of results obtained. (Rahman et al., 2026; Ang, 2025). This perspective extends previous studies advocating performance-based assessment by proposing that DTs can continuously capture evidence of learner decision-making, adaptation, and professional judgement within authentic engineering contexts.

However, there is also the bridging function, and this is becoming more evident. Where DTs are involved and there is real or representative information regarding their operation, there is a beginning to represent the constraints and expectations of professional environments. This creates a space in which academic and professional worlds overlap naturally. Projects and collaboration are no longer divorced from the learning process; indeed, collaboration is facilitated within the learning process. This integration of the two worlds means that the distinction between education and the industry is not clearly defined; indeed, the engagement is not superficial but is maintained (Grieves & Vickers, 2016; Zhang et al., 2025). Consistent with previous research highlighting the importance of stronger industry–academia collaboration, the proposed framework embeds authentic engineering contexts directly within the learning process rather than treating professional engagement as an isolated curricular activity.

Accordingly, Figure 3 presents the conceptual framework developed in this study. The framework integrates learning, assessment, industry engagement, and AI within a unified DT environment, thereby extending existing educational perspectives into a coherent model for practice-oriented engineering education. AI functions as the enabling layer that enhances adaptability, personalised feedback, and scenario complexity, reinforcing the educational role of DTs as dynamic learning infrastructure rather than standalone technological tools.

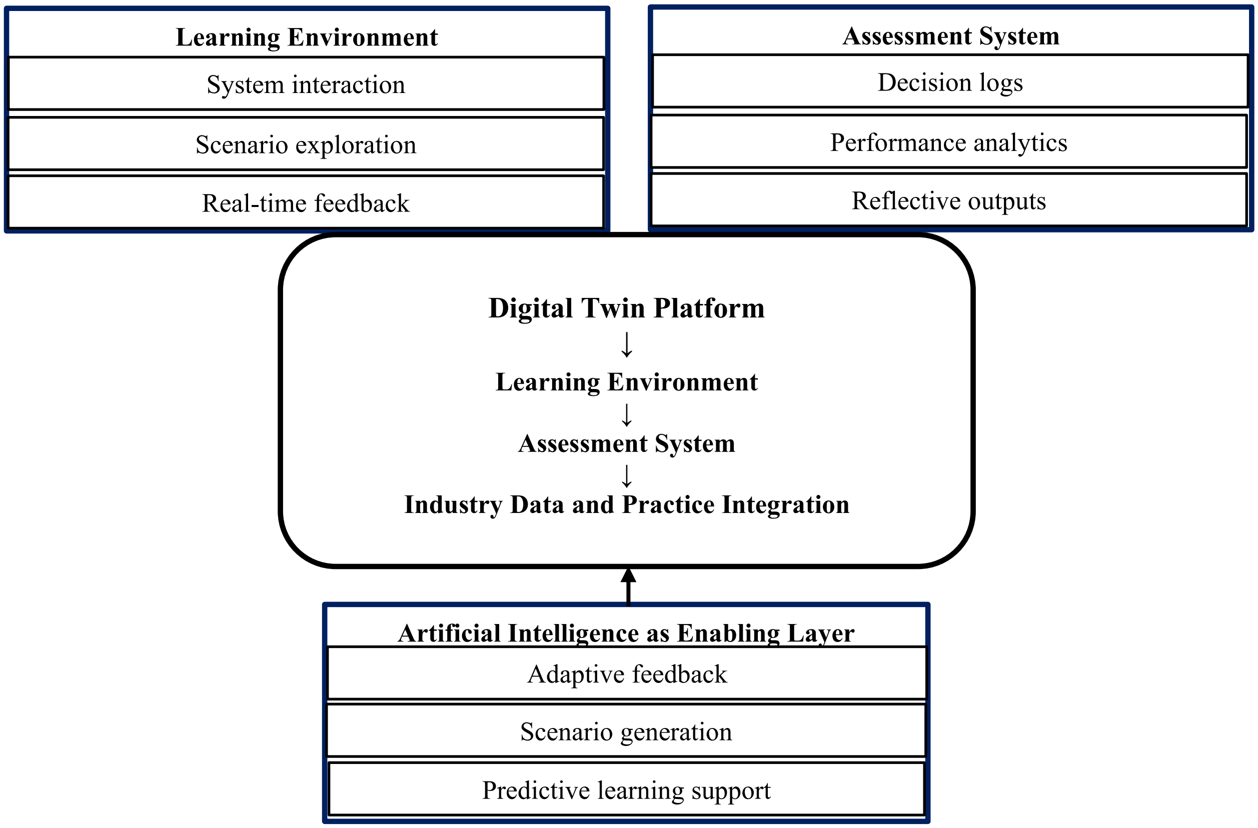

Figure 3. AI-Integrated Digital Twin Framework as Educational Infrastructure.

4.2. AI-Integrated Learning Architecture

At the heart of the envisioned framework is AI, not as a feature to be added but as a level through which the system thinks, adapts, and reacts. Its purpose goes beyond computation. It is not envisioned as an opaque optimizer but rather as a mediator connecting data input, model use, and student decisions in a way that is clear and transparent. Building upon recent studies on AI-enabled learning environments, the proposed architecture positions AI as the cognitive layer that supports adaptive learning, informed decision-making, and continuous interaction between learners and DTs. What is significant here is not functionality but how functionality impacts learning.

One of the more immediate effects of this integration is the ability to produce scenarios that might otherwise be hard to produce. The state of the system may change in reaction to the actions of the learner. This may be sudden or gradual. The ability to produce unusual scenarios, failures, edge cases, or high-risk situations without warning is also possible. This generates a different type of learning environment wherein the student must learn to navigate through uncertainty without precedent. This fosters a more cautious approach to reasoning (Liu, 2025; Liu & David, 2025; Syarifuddin et al., 2025). Accordingly, these studies suggest that AI enables authentic learning experiences by exposing students to complex engineering situations that are difficult to replicate using conventional teaching methods.

With this, monitoring goes on continuously but not in an evaluative capacity. Instead, patterns start to appear through the interaction with the system. This includes the timing of the decisions, the approach used by the students,

and the nature of the mistakes. This is not provided in isolation but rather integrates with the feedback. The feedback will adapt in real-time. The students will be provided with guidance but will not be forced to do so. This will ensure development without eliminating the necessity of judgment itself (Kotecha et al., 2025; Rahman et al., 2026). In this way, assessment becomes an ongoing learning process rather than a single measurement of performance, supporting continuous reflection and progressive competency development.
However, another aspect to be considered, which is sometimes not taken into account in the development of the technology, is the way in which the AI communicates the results. In the proposed system, the opacity of the results is not an advantage. Instead, the results are explained in such a way that the assumptions and the uncertainty do not remain hidden. This is also not just for the development of the technology. This is for the students as well. This way, the students can question the results as they are presented to them, rather than simply believing them. This is not just for the development of the technology. This is for the students as well. This way, the students can question the results as they are presented to them, rather than simply believing them.

This emphasis on explainability aligns with recent discussions on trustworthy AI, which advocate that learners should understand how AI-generated recommendations are produced rather than simply accepting them as correct. This is not just for the development of the technology. This is for the students as well. By making assumptions, uncertainties, and decision pathways visible, students are encouraged to question AI outputs, evaluate alternative interpretations, and exercise independent engineering judgement. Consequently, the proposed AI architecture extends existing educational applications of AI by integrating adaptive learning, transparent reasoning, and reflective decision-making within a single DT environment, thereby strengthening both technical competence and professional responsibility.

4.3. Practice-Oriented Learning Cycle

Rather than distinguishing between theory and application, the framework proposes to conceive of the process of learning as a continuous cycle of testing and revisiting ideas. The goal is not to mimic professional practice in any literal sense but to approximate the way engineering knowledge is progressively constructed through authentic practice, reflection, and iterative decision-making. This perspective builds upon experiential learning and constructivist theories discussed in Section 3, where learning is viewed as an active and continuous process rather than a sequence of isolated instructional events. What is created is a process of learning that is at once embedded in pedagogy and captures the essence of the continuous cycle of engineering practice.

The process usually starts with a point of orientation. Basic principles are introduced, though not in great depth, just to the point of getting the process started. Then, the focus is immediately placed in the DT world, where the principles are brought to life. Students explore, and the experience is not always immediately or necessarily easily predictable. Decision-making is next, though it is not necessarily a standalone process. Decisions must be made, and in some cases, decisions must be un-made as the system response dictates.

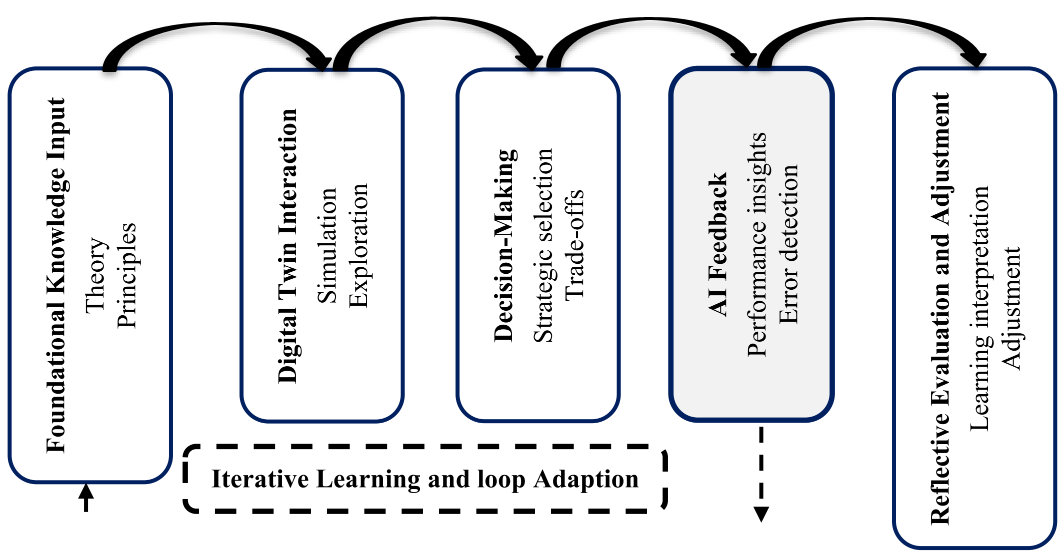

Figure 4. AI-Integrated Practice-Oriented Learning Cycle in Digital Twin Environments.

Only then does reflection emerge, but not in a passive sense. The analytics provided by AI have already made some aspects of the decision-making process transparent: how decisions were made, what the results were, and how they differed from what was intended. This stage of the cycle often has a slowing effect on the process. It prompts a kind of review. The learner starts to make more deliberate connections between decisions and results, often becoming aware of what they have failed to consider. These are critical elements of the cycle because they enable the transfer of what has been learned to new situations and promote a more reflective kind of practice (Makransky & Petersen, 2019; Pathak & Upadhyay, 2024; Ang, 2025). This cycle becomes more intense with repetition. The process of learning facilitated by AI-based DTs is an iterative process. Figure 4 illustrates this process of learning. Students go through a cycle of understanding concepts, interacting with systems, making decisions, and reflecting on their decisions with the support of AI-based feedback systems.

4.4. Curriculum Mapping and Learning Outcomes

For the framework to be effective beyond individual activity instances, integration of the framework components into the curriculum structures is a necessity. This means that the activities, which are centered around the use of DTs, are aligned to specific outcomes to ensure that the use of DTs is central and not peripheral. Consistent with recent studies on curriculum innovation in engineering education, this alignment ensures that DTs and AI are embedded as integral components of learning rather than supplementary instructional technologies (Álvarez & Hernández, 2026; Ang, 2025). There are a number of outcomes associated with this. Knowledge acquisition, although still relevant, is no longer seen as the only factor, and it is now taken into account together with technical, ethical, and professional aspects. Based on this synthesis, the proposed curriculum mapping promotes a balanced development of technical competence, critical thinking, ethical reasoning, and professional judgement, reflecting the multidimensional expectations of contemporary engineering graduates.

Another variation arises due to the differences in educational levels. In the case of an undergraduate student, the process of learning is more structured. The student gets accustomed to systems and becomes conceptually clear. The student also starts to make decisions in a structured environment. However, in the case of postgraduate students, yet again, the scenario changes. The student is given more freedom, and the situation becomes less predictable and even interdisciplinary in nature (Álvarez & Hernández, 2026; Ang, 2025; Liu, 2025). These observations are consistent with existing literature, which recognises that learning activities should progressively evolve from guided practice towards independent, interdisciplinary problem-solving as learners advance through different educational stages.

What is avoided through such a mapping is the phenomenon of fragmentation. Learning in the form of AI integration and the practice-oriented nature of it is not added as another component of the curriculum. Instead, it becomes one of the principles of the curriculum. Building upon the literature synthesised in this study, the proposed framework integrates curriculum design, learning activities, assessment, and industry engagement within a coherent educational structure, thereby reducing fragmentation and strengthening the alignment between engineering education and contemporary professional practice.

5. Educational Implications and Implementation Pathways

In order to translate the proposed framework into practice, flexibility rather than prescription is called for. This is because institutions vary in resources, priorities, and even disciplinary focus, sometimes considerably. Consistent with the literature on curriculum innovation and engineering education reform, successful implementation depends on adapting educational strategies to institutional contexts while preserving their underlying pedagogical principles (Álvarez & Hernández, 2026; Ang, 2025).

It is for this reason that what is proposed next is not a single implementation model but rather a set of pathways, which are to be adapted, adjusted, and even reinterpreted to suit local conditions while at the same time maintaining the principles of the proposed framework. Building on this conceptual framework, the following implementation pathways are intended to provide flexible guidance for integrating AI-enabled DTs into engineering education while supporting curriculum coherence, authentic learning, and industry relevance across diverse educational settings.

5.1. Curriculum Design Implications

The integration of AI-based DTs in the engineering curriculum necessitates a transition from traditional course-centred curriculum design towards an integrated, programme-wide learning model. Rather than introducing DTs through isolated courses or elective modules, existing literature increasingly supports their progressive integration across multiple stages of engineering education to strengthen continuity between theoretical knowledge and professional practice (Negahban, 2024; Liu, 2025; Karanam, 2025). Accordingly, the integration of DTs with AI cannot be accommodated by adding courses in isolation. A more holistic view is necessary. While the integration of DTs in electives or individual courses is limited in its scope and impact, the proposed framework advocates their systematic incorporation throughout the curriculum. The initial stages might include the use of DTs to a limited degree, primarily to develop conceptual understanding, whereas the latter stages gradually introduce more complex DTs, AI-supported decision-making, and authentic engineering scenarios.

However, there are also strategic opportunities within existing programs to integrate DT technologies with minimal disruption. For example, capstone projects represent a potential integration point. By their nature, these projects occur at the end of the undergraduate experience and already require students to integrate concepts, apply knowledge, and think independently. By introducing AI-enabled DTs in these environments, another dimension is added to the experience as students engage with systems that change, react to their decisions, and sometimes challenge their proposed solutions. Consistent with previous studies on practice-oriented engineering education, this approach strengthens students' ability to apply theoretical knowledge within realistic and evolving engineering contexts (Álvarez & Hernández, 2026; Ang, 2025).

To facilitate practical implementation, the proposed framework is accompanied by a structured institutional implementation pathway. Figure 5 illustrates the six-stage implementation model developed in this study, beginning with curriculum assessment, followed by faculty development, pilot implementation, industry integration, continuous evaluation, and full institutional deployment. The model is intended to support phased adoption while allowing institutions to adapt the framework according to their educational priorities, available resources, and organisational context.

5.2. Assessment and Evaluation Strategies

If the process of learning is altered, then the process of assessment cannot remain the same. In a conventional process of assessment through tests and examinations, correctness and speed are key factors. However, recent studies on engineering education increasingly advocate assessment approaches that capture learners' reasoning, adaptability, and decision-making processes in addition to technical accuracy (Rahman et al., 2026; Syarifuddin et al., 2025). In this regard, the proposed framework repositions assessment as a continuous process that evaluates learner development over time rather than isolated performance at a single point. DTs facilitate this by tracking the manner in which the learner interacts with the system, that is, the sequence of decisions made, decisions altered, and moments of indecision. Such evidence provides a richer representation of engineering competence by documenting how learners interpret information, respond to uncertainty, and refine their decisions within authentic engineering contexts.

In this regard, AI is seen to play a supportive role rather than a substitutive role. It is possible to track patterns of learner behavior and provide adaptive feedback based on those learning patterns. Here, the role of AI is not to replace judgment but to strengthen judgment through timely insights, reflective prompts, and personalised guidance. Ultimately, the process of assessment is presented as a curated collection of decisions and outcomes across various scenarios. Consistent with emerging perspectives on AI-supported assessment, this approach values both the quality of learner decisions and the reasoning underpinning those decisions, thereby promoting greater transparency, accountability, and reflective learning (Kotecha et al., 2025; Syarifuddin et al., 2025).

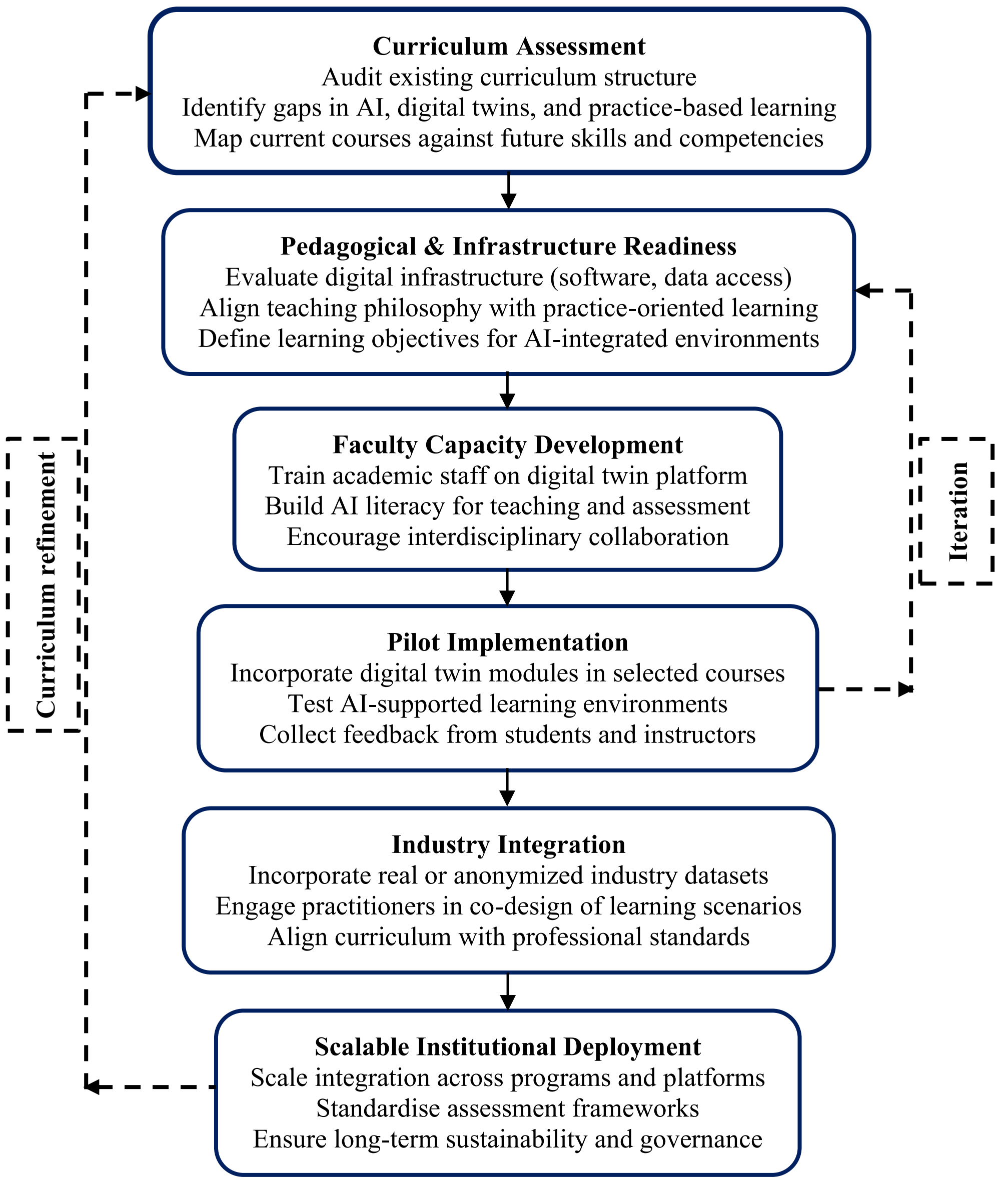

Figure 5. Six-Stage Institutional Pathway for Implementing AI-Integrated Digital Twin Learning.

5.3. Industry–Academia Collaboration Models

The existence of DTs, furthermore, has implications for how engagement with industry might be achieved, shifting collaboration beyond traditional internships towards continuous educational partnerships. This is because of shared digital learning environments, through which datasets, appropriately anonymised operational data, engineering constraints, performance indicators, and industry benchmarks can be incorporated into authentic learning activities. Consistent with previous studies, such collaborative environments enable engineering education to reflect contemporary industrial practice while maintaining academic integrity (Grieves & Vickers, 2016; Jebelli et al., 2024).

The nature of such participation may also vary. Practitioners are no longer just contributors from outside; they are also able to contribute to the design of the learning activities themselves. This ensures that the learning activities remain relevant to the changing demands of the profession. At the same time, there is greater relevance for the institution since the industry has a more direct say in the formation of expertise for the future. The relationship is no longer transactional; it is more collaborative in nature (Álvarez et al., 2023; Ang, 2025).

5.4. Applicability Across Global Contexts

Another practical concern relates to the ability of the institution to provide high-fidelity DTs and advanced AI. The framework does not assume the availability of such facilities. Instead, it offers the flexibility for the implementation of varying levels of these technologies. In some environments, the availability of high-fidelity solutions might be possible, while in others, the use of simple architectures with the help of open-source tools and AI might provide opportunities for learning (Syarifuddin et al., 2025; Pathak & Upadhyay, 2024).

This is the main idea behind the importance of the framework. At the same time, this is the reason why the framework is not aligned with any technology. Instead, the focus is on the underlying principles. As a result, the framework is applicable across a wide range of educational institutions, ranging across the Global South and Global North, while engaging meaningfully with the idea of progressing further with more practical forms of engineering education (Álvarez & Hernández, 2026; Daineko et al., 2025).

6. Discussion, Future Directions, and Conclusion

What is presented below is not simply a repetition of the arguments discussed previously. Rather, it is an attempt to synthesize these arguments and subject them to an analysis and to define the areas within which these arguments are applicable. The goals of this section are to assess the contribution of the framework and to contextualize the framework within the general context of engineering education.

6.1. Educational Value and Theoretical Advancement

At its core, the framework redefines the role of DTs in the educational domain. DTs are no longer at the periphery of the learning process; rather, they are at the core of the pedagogical process. This is a major change. DTs, when linked to AI-based feedback, scenario adaptation, and performance updates, are not simply a tool for learning but a means of learning. This is an extension of the potential of experiential and constructivist learning through the facilitation of interaction through data and AI (Negahban, 2024; Syarifuddin et al., 2025; Kotecha et al., 2025).

There is also a shift of emphasis of a kind that is both subtle and important: the concept of learning is no longer defined simply in terms of the development of competencies; it is also defined in terms of decision-making, often in conditions of uncertainty. In that respect, it is a question of focusing on forms of judgment that are hard to formalize in any traditional way; systems thinking, ethical awareness, and professional responsibility are no longer considered as secondary aspects of the learning process; they are considered as integral aspects of it.

6.2. Challenges and Limitations

However, the transition from concept to implementation is not expected to be smooth. This is particularly true in the case of institutional capacity. There is a possibility that the programs might not have the necessary infrastructure to adopt such an approach. Even if there is availability of resources, there is no guarantee.

Another issue of concern is the place of the technology. There is a subtle bias where the tools are dictating the agenda for education, rather than the converse. If this is not addressed properly, there is a risk that AI-driven learning analytics may oversimplify complex learning processes of technological determinism where the impetus for adoption is based on capability rather than necessity (Rahman et al., 2026).

However, there is another dimension of complexity related to ethical considerations. There are learning spaces facilitated by AI support that are dependent on data, at times large amounts of data and at times data of a sensitive nature. There are issues of governance and bias that cannot be relegated to a secondary level. This is particularly true, as Syarifuddin et al. (2025) and Lin et al. (2025) point out, since there is a potential specter of learning analytics oversimplifying complex processes and creating inequalities. It is not simply a matter of security considerations but also one of making sure there is a clear consideration of the role of values.

6.3. Future Research Directions

Some lines of inquiry for future research could be proposed based on the current research. One of the first concerns is the empirical validation of the proposed framework. Even though it has a strong foundation in theory, it is also important to consider how it could work in terms of different disciplines and settings. It is also possible to conduct a comparative analysis of the outcomes to understand the impact of different conditions on the outcomes of the learning process and the engagement and preparedness of the learner. Another dimension to consider is the analysis of the outcomes over time. For instance, the long-term impact of interaction with AI-based DTs on professional identity and ethical decision-making is of interest. Although these outcomes may not be readily visible, they are of interest in terms of the long-term impact of the educational reform.

It is also important to consider the practical aspects of the issue at hand. For instance, the development of open platforms is of major interest in terms of the promotion of the framework and its adoption in resource-constrained contexts. Such developments are unlikely to be conducted in isolation; rather, a collaborative approach is necessary to improve and advance the framework and to define standards for its application (Daineko et al., 2025; Omrany et al., 2026).

6.4. Conclusion

There are, of course, some moments when change is no longer incremental. The field of engineering education, it seems, is approaching one of those moments. As the use of DTs and AI continues to reshape the professional landscape, the framework through which engineers are educated cannot help but change as well. This conceptual article has outlined one alternative approach. By recognizing the role of the DT as part of the educational framework, and the role of AI as part of the educational process, the framework redefines the very notion of learning engineering. The focus moves, for example, from the use of technology to the use of system, and from the solution of known problems to the solution of unknown problems.

If implemented correctly, the potential impact is not merely on the curriculum but on the very essence of how the engineers of the future think, how they make decisions, and how they embrace the burden of responsibility for the increasing complexity of their creations. In this sense, the framework is not merely aligned to the current practice but is aligned to the potential for creating engineering education frameworks that are not merely resilient, relevant, and adaptable but resilient, relevant, and adaptable to whatever comes next.

Declarations

Acknowledgments
The author expresses sincere appreciation to Final International University for providing an enabling academic environment and tools to support the development of this study. No external funding was received for this research.

Competing Interests
The author declares no known competing interest that could have appeared to influence this study.

Ethical Statements
The study did not include human participants, animals or any personal data collection. Therefore, ethical approval and Institutional Review Board (IRB) approval were not required.

Author Contributions

Author[1]: Conceptualization; Investigation; Literature review; Writing original draft; Supervision; Methodological refinement; Visualization; Validation; Writing review and editing.

Data Availability

No primary datasets were generated or analysed during the current study. All information used in this research is derived from publicly available sources cited in the reference list.

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