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ADAPTIVE AI-DRIVEN PLATFORMS FOR PERSONALIZED ONLINE ENGINEERING EDUCATION: A CONCEPTUAL FRAMEWORK FOR SKILL DEVELOPMENT

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Abstract:

This paper proposes a conceptual framework for adaptive AI-driven platforms in online engineering education, designed to support personalized, skill-oriented, and experiential learning. Conventional online learning models often struggle to accommodate differences in learners' prior knowledge, learning pace, and the practice-intensive nature of engineering education. Addressing these limitations, the study adopts a theoretical and integrative approach that synthesizes insights from online learning research, artificial intelligence in education, and engineering pedagogy to develop an adaptive framework comprising five AI-enabled components: a Learning Analytics Module (LAM), Adaptive Content Delivery System (ACDS), Intelligent Tutoring System (ITS), Virtual Lab and Simulation Integration (VLSI), and Personalized Assessment Engine (PAE). The proposed framework enables continuous learner profiling, adaptive instructional sequencing, context-sensitive tutoring, simulation-based experiential learning, and personalized assessment through analytics-driven feedback loops. By explicitly linking conceptual understanding, hands-on practice, and skills assessment, the framework addresses key challenges in online engineering education, including feedback latency, learner disengagement, and high dropout rates. The paper also discusses implementation considerations related to data privacy, ethical AI, infrastructure requirements, faculty readiness, and system integration. The novelty of this work lies in its engineering-specific adaptive

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architecture, which extends general Artificial Intelligence in Education (AIED) models by integrating cognitive, experiential, and application-oriented learning dimensions, and provides a foundation for future empirical validation in higher education contexts.

Keywords:

Adaptive AI Systems, Engineering Education, Online Learning; Learning Analytics, Personalized Adaptive Learning, Intelligent Tutoring Systems, Virtual Laboratories

Introduction

Change wrought by technology and the need for more flexible, accessible higher education is disrupting the industrial model of college. Previously, online learning was considered supplementary, but now it is at the core, particularly in areas like engineering, where a lot of hands-on experience and complex problem-solving are required. However, successfully delivering engineering education on the internet poses unique challenges. Engineering programmes are traditionally cumulative; hence, adequate understanding of the basic concepts, laboratory application, and development of complex problem-solving skills are crucial (Wankat & Oreovicz, 2015). At the same time, the traditional and many of the current online models have a "one-to-many" problem that does not take into account the individual learning needs, prior background disparities, and diverse cognitive paces for the students (Means, Toyama, Murphy, & Baki, 2013).

Rapid advancement in disruptive technologies such as Artificial Intelligence (AI) have gifted us the ability to process data, modulate behaviour and deliver intelligent experiences like never before in many industries. In education, AI has substantial potential to progress from static content delivery to dynamic individualized learning experiences (Holmes, Bialik, & Fadel, 2019). Although AI in university general education is now becoming popular, the incorporation of AI in online engineering education, not the AI applications in online engineering education from general higher education, especially for the systematic development of different skills, is still an open question as well as area for investigation and work.

This paper presents a new approach for exploiting adaptive AI online for an innovative personalized educational engineering. This work contends that well-designed AI systems can enable personalized learning environments, which adapt on-the-fly to individual student performance, engagement, and learning style, to more effectively achieve the theoretical knowledge and practical skills that future engineers will need. The main contributions of this paper are the definition of a framework for such platforms, the description of AI mechanisms required to achieve full personalization, and the presentation of the pros and cons of their usage.

Methodology

This paper adopts a theoretical and conceptual approach to present a new model for personalized engineering education through AI-driven adaptive educational platforms. Drawing from published work on online learning, AI in education, and engineering pedagogy, this work provides a synthesis that will contribute to the development of an encompassing conceptual structure. It starts by looking at existing systems and technologies and their constraints in engineering domains, then defining how an AI-enabled platform would shape up

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based on the same. No empirical analysis is performed; this paper only concerns the design of the framework, system components, and theoretical conceptualisation.

The nested structure of the proposed conceptual approach facilitates iterative interactions among emerging themes across disciplinary practices, integrating instructional design, artificial intelligence, and specialized educational domains, particularly engineering education. Conceptual frameworks of this nature are especially valuable for theory building and for guiding future empirical investigations.

Background and Related Work

The development of Engineering Education Online

Engineering education has undergone a revolution in the last 10 to 15 years, from being little more than an electronic warehouse for lecture notes and slides to 'full-blown' Learning Management Systems (LMS), with features such as interactivity, discussion forums, and virtual collaboration tools. The causes of this migration are relatively simple: more access is being opened up; lifelong learners are better served; and digital offerings have forced that old classroom to change, regardless of who else shows up. However, although already present in the modality of online engineering education, other dimensions that remain to be improved include high abandonment rates, a lack of practical experience, and insufficient individualized support (Xavier & Meneses, 2020). Due to the complex engineering discipline domains and practices involved, a gap may exist between the theoretical education provided through online learning and its practical application.

In the broader landscape of digital transformation and efforts to democratize engineering education in online spaces, accessibility, flexibility, and learner autonomy emerge as key building blocks. Traditional engineering sciences such as electrical engineering and electronics have introduced hybrid teaching methods in recent years via blended learning for combination of theoretical oriented university-articulation courses and vocational applications. However, even as educational technologies have progressed, the challenge of enabling truly experiential learning in a completely remote setting remains. As a result, there is also an increased need for platforms offering organized and adaptable learner support tailored to asynchronous engagement patterns and non-uniform educational experiences across the engineering student body (Means & Neisler, 2020).

The Emergence Of AI In Education (AIED)

The field of AI in Education (AIED) has grown significantly over the last ten years: from early intelligent tutoring systems (ITSs) to current adaptive learning environments, automated assessment tools, and learning assistance (LA) dashboards (Holmes et al., 2019; Leong, Leong, and Leong, 2025). Early ITS systems, such as SCHOLAR and SOPHIE, were among the first to focus on student knowledge modelling and providing instructive feedback, unlike teacher-focused Educational Technology (Carbonell, 1970). AIED has evolved since then, as artificial intelligence-based technologies have advanced to create AIED systems that are much more ambitious and complex.

Machine learning, natural language processing, and computer vision, among other technologies, enable a more data-driven and personalized educational experience. Machine learning techniques are also widely applied for predictive analytics, such as predicting at-risk

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students and providing personalized learning paths and recommendations by analyzing learners' behaviour (Isaeva, Karasartova, Dznunusnalieva, Mirzoeva, & Mokliuk, 2025). Society has achieved a similar feat with natural language processing, which fuels intelligent conversational agents, automates the scoring of free-text questions, and delivers personalized feedback at scale (Kumar & Howard, 2024; Somers, Cunningham-Nelson, & Boles, 2021). Likewise, computer vision technologies are a value-added tool for AIED applications, enabling the monitoring of learner engagement in virtual environments and providing gesture-based interaction/tutorial simulation, or skill training in computer-based/virtual laboratories (Duraisamy et al., 2019; Huy, Carlon, Cross, & Nguyen, 2022).

Even though these AI-enabled applications have proven helpful in various educational settings, their adoption in online engineering education has not been straightforward. Engineering education is inherently multimodal, involving the concurrent development of conceptual understanding, iterative problem-solving skills, and hands-on competencies. Current adaptive AIED systems are mostly general-purpose and may lack the sophistication to accommodate the cognitive complexity, kinaesthetic involvement, iterative feedback loops, or concept development process important for engineering learning. While AI systems can sequence learning content, determine pacing of the curriculum for an individual learner, analyze discourse or interaction, and engage students within Learning Management Systems (LMS), their practical implementation in engineering education is yet a challenge due to the depth of processing cognitive information and experiences that are needed (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019).

The Need for Personalized Adaptive Learning in Engineering Education

Computer-based engineering education presents its own pedagogical challenges and is, therefore, indeed one of the strongest adapted learning domains. Students who join engineering programs come with a wide range of prior knowledge in basic areas such as mathematics, physics, and computing. This results in differential learning transition with the possibility of repeating some courses (Babu Lal, 2023). These differences are exacerbated by the abstractive nature of many engineering concepts, which require the integration of multiple perceptual modes, visual, auditory, and kinaesthetic, to facilitate deep learning (Min, Jackman, & Zugg, 2017).

Along with its cognitive aspect, engineering education is inherently practical. In engineering learning activities, students apply their knowledge in practice through cyclic problem-solving, laboratory experiences, and design exercises. The challenge in the current environment is replicating such experiences in fully online settings, particularly when learning tasks are hands-on and involve real-time feedback (Vidalis, Subramanian, & Najafi, 2024). In addition, the significant variability in terms of progression, self-regulation, and instructional support needs among students may alienate some from one-size-fits-all instruction based on a single average level (Baguley et al., 2014).

The set of pedagogical difficulties is complicated by the high-speed evolution in engineering areas, driven by technological changes, which implies continuous development of skills and updating of curricula. Personalized learning approaches can help students quickly adapt to new technologies and meet the evolving needs of changing industries by offering instruction tailored to personalized, progressive paths (Mazumder, Chen, & Sultana, 2020). The provision of timely and personalized feedback at scale (especially for more advanced engineering

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exercises or the hands-on lab work) is, however, a significant issue in present online learning systems, which results in feedback delay that diminishes the effectiveness of learning.

These limitations are surpassed by adaptive AI-based systems, which move from displaying static content to offering dynamically changing learning contexts where the (dynamic) learner profiles will be able to endure. These spaces enable the personalization of pace and sequencing of content, with feedback loops that support a bias for action, leading to an integrated doing–learning loop. In the broader global context of a move towards competency-based education and away from centralised mechanisms for assessing skills, adaptive platforms provide a possible mechanism to monitor systemically and scaffold learning outcomes in such a way as to drive not only alignment between meso-level skills and industry-desired competencies, but job-ready graduates (Mistee et al., 2013).

Additionally, engineering education is typically delivered in a collaborative learning environment, featuring projects and teamwork-based problem-solving exercises. With AI support in learning platforms, personalization at scale can also be made possible in these environments by providing engagement analytics and individual-level adaptations within social contexts. This enables a more successful scaffolding of group processes, promoting both individual accountability and group performance in complex engineering problems (Chen, Xie, Zou, & Hwang, 2020).

Proposal for Adaptive AI-Based Engineering Education Platforms

This paper aims to propose a conceptual model for AI-driven adaptive platforms specifically developed for online engineering education, with the goal of personalised experiential and skill-based learning. In contrast to the general-purpose AIED models, which assume no specific knowledge domain and have been built independently of any framework intended for learning in general, there are specific requirements for engineering education, where, for example, the knowledge domain must be closely linked to active practice and feedback loops.

This framework, Figure 1, views the structure of adaptive learning as a multidimensional, dynamic process centrally mediated by intelligent components and their interconnected AI-based capabilities, rather than as an accumulation of independent instructional solutions.

Narrative Explanation of Figure 1

Figure 1 presents the conceptual architecture of the proposed adaptive AI-based engineering education platform, organized around a central Learning Analytics Module (LAM). The arrows in the framework represent continuous feedback-driven information flows that support adaptive regulation, rather than static or linear data transmission. Learner interactions captured through the Student Interaction Interface—including content access, problem-solving attempts, simulation activities, and assessment responses—are continuously fed into the LAM. Based on this data, the LAM dynamically updates learner profiles and regulates the adaptive behaviour of the core system components.

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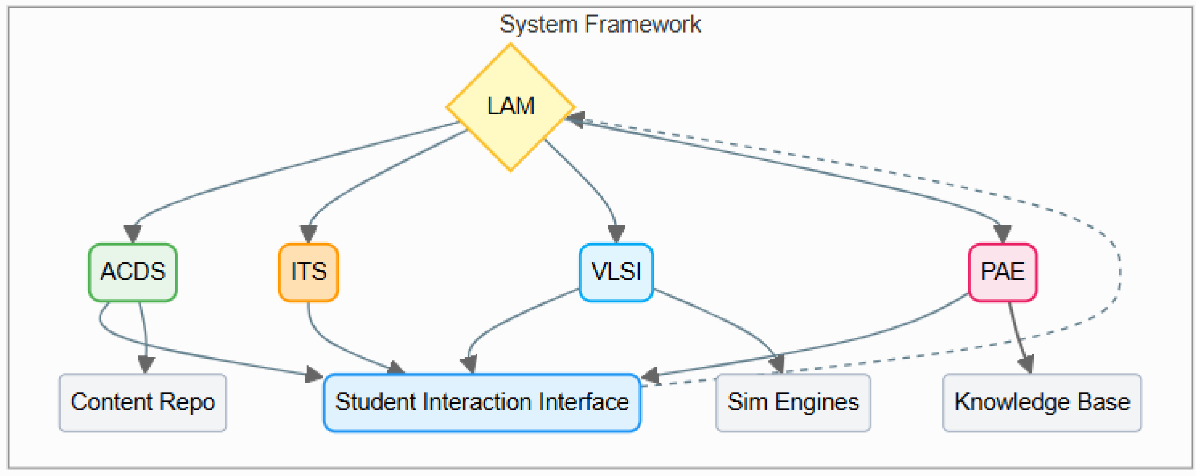

Figure 1: Conceptual Framework for Adaptive AI-Driven Engineering Education Platforms

The outgoing arrows from the LAM to the Adaptive Content Delivery System (ACDS), Intelligent Tutoring System (ITS), Virtual Lab and Simulation Integration (VLSI), and Personalized Assessment Engine (PAE) indicate real-time personalization decisions related to instructional content, tutoring interventions, experiential practice, and assessment adaptation. In turn, learner interactions mediated through these modules—captured via the Student Interaction Interface—generate interaction and performance data that are continuously fed back into the LAM, forming closed feedback loops that enable ongoing refinement of instructional strategies. This cyclic interaction distinguishes the framework from linear or one-directional AIED architectures.

Three-Dimensional Learning Effects and Distinction from General AIED

This model can have a three-dimensional zone of proximal development, which is not possible with the classic AIED models described above. The first problem is a cognitive one, which can be addressed by adaptive content sequencing and an intelligent tutoring system, as learners can receive support to understand concepts depending on their different prior experiences and learning pace. Second, this 'hands-on' aspect is facilitated by the use of virtual labs and simulations, which provide students with the opportunity to practice experimentation at an engineering educational level. Third, the situational learning aspect is supported by individual skill evaluations and problem-solving drills to solidify concepts that are well understood.

In contrast to the more traditional AIED systems that apply adaptation on several separate levels of instruction, these three levels are intertwined with learning analytics-driven feedback loops running continuously under the control of the Learning Analytics Module, leading to a fully integrated, engineering-specific, adaptable learning environment.

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Table1: Functional Interactions Among Framework Components

Component	Primary Role	Input to LAM	Output from LAM
Learning Analytics Module (LAM)	Central learner modelling and adaptation hub	Learner interactions, Assessments, simulation data	Adaptation signals to all modules
Adaptive Content Delivery System (ACDS)	Personalized content sequencing and pacing	Usage and engagement data	Adaptive content recommendations
Intelligent Tutoring System (ITS)	Context-sensitive guidance and scaffolding	Problem-solving behaviour	Hints, feedback, tutoring actions
Virtual Lab & Simulation Integration (VLSI)	Experiential and practice-based learning	Simulation performance data	Adaptive scenarios and practice tasks
Personalized Assessment Engine (PAE)	Adaptive evaluation and competency mapping	Assessment outcomes	Diagnostic feedback and mastery updates

Conceptual Explanation of the Adaptive AI Framework

The Learning Analytics Module (LAM) is at the heart of the framework, serving as an intelligent control centre that continuously collects, processes, and interprets users' interactions. Instead of a simple report generation application, LAM is an application capable of live learner modelling by collecting engagement patterns, performance metric alerts, learning behaviour preference indicators, and behavioural signal data, which leads to the formation of student profiles. These profiles are responsible for the adaptive behaviour of all other members of the system, permitting dynamic changes in learning situations (Maseleno et al., 2018).

The theoretical contribution of the model lies in offering a three-dimensional learning effect (cognitive, experiential, and application learning), as two-dimensional effects currently represent existing constructs. There is cognitive scaffolding provided by adaptive content sequencing and intelligent tutoring systems that can be adjusted according to the instructional offer to learners' prior knowledge, pace of learning, and their perception interface. This is achieved through a series of virtual labs and simulations, where students experience practice-based inquiry, experimentation, and design, key elements in engineering educational pedagogy. The applicability dimension is addressed through individualized assessment and feedback to monitor not only what learners know but also how skilful they are at solving problems.

These three components are not treated as distinct layers, yet they interact with each other through mutual feedback within the LAM. This student interaction surface records various student interactions with learning modules, tutoring sessions, simulations, and assessments, which are stored in the analytics core to provide real-time feedback for the system to modify its instructional strategies. This two-way structure contrasts with many traditional AIED systems, where adaptation occurs only at either the instruction level (i.e., transmitting content

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or testing) or, at the very least, without consideration of both experiential learning and skills deployment within the same adaptive loop.

In this architecture, the modality, complexity, sequence, and timing of delivery are personalized to Learning profiles produced by ACDS from LAM (Isaeva et al., 2025). An ITS has been established to provide domain-specific assistance, such as hints, scaffolding, and feedback support, for the advanced engineering problem-solving process. In addition to these, the VLSI module features Virtual Lab and Simulation Integration (VLSI) to create an experience-based learning environment that connects theoretical teaching with practical skills. This is complemented by the Personalized Assessment Engine (PAE), which offers contextually adaptive assessments with feedback, difficulty, and competence mapping to match each learner's unique path.

Unlike current, more generic AIED systems, which have focused on maximizing the amount of content delivered or learner engagement statistics, the framework described is interested in instruction that has coherence across learning objectives and between practice and assessment activities. All models are tied to explicit instructional goals, which guard against personalization being mindless and random. Instead, they engage in a disciplined process of skill acquisition. A further benefit is that the modular nature of the platform can be expanded to other engineering sub-disciplines, as well as institutional needs problems (e.g., accreditation), without compromising pedagogical integrity.

Finally, the framework is organized by inclusion principles to accommodate linguistic, cultural, and experiential diversity among engineering learners. These adaptive interfaces, multilingual assistance, and interactive feedback mechanisms are implemented to support equitable interaction with and application of the systems described here. Through the integration of quality into system adaptation logic, this framework supports the dissemination of large-scale AI-enhanced learning innovations. In addition, they help to address issues of fairness and access in online engineering education (Holmes, Bialik, & Fadel, 2023).

Implementation Considerations and Challenges

Although the application of learning systems based on adaptive AI has its practical, ethical, and institutional considerations as well that require some reflection to support uptake, primarily responsible and sustainable use, data privacy, and security are of the most important concerns, because these platforms can only function if they get their hands on sensitive student information. Institutions' informed consent policies should also require that learning data is sufficiently secured _ a robust system of encryption and anonymization protocols, and fully compliant with relevant laws, such as the General Data Protection Regulation (GDPR) or Family Educational Rights and Privacy Act (FERPA). Transparent policies regarding the use, storage, and access of data are crucial for establishing trust between students as users and both lecturers and their institution (Nantsou et al., 2025). The ethical implications of AI should also be factored in. In the process of learning or inference, a model may not only inherit but also amplify the bias in the training data. The only way these issues can be addressed successfully is if ethical and responsible AI becomes the norm, when models are trained on diverse, fair datasets, and when "Explainable AI" (XAI) techniques enable us to understand how an algorithm has made a decision, and when humans are always in charge. Teachers need time to thoughtfully consider AI-generated recommendations and assessments, as well as the authority

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to intervene when something is out of line with equity or what makes sense pedagogically (Liu et al., 2025).

Another critical point for successful implementation is the readiness and acceptability of teachers. With the advent of adaptive AI systems that adapt and develop over time, educators' roles shift from 'delivering information to students' to managing and interpreting analytics, as well as designing AI-mediated learning experiences. This kind of transformation in schools will depend on ongoing professional development for teachers, enabling them to become critically engaged with tools and learning analytics. The fear of replacement due to job loss or a loss of professional freedom could also be mitigated by introducing AI as an adjunctive aid, complementary to the work teachers do, rather than replacing it (Nikitina & Ishchenko, 2024). There are technical limitations of the infrastructure and scalability issues. Adaptive AI needs enormous computational resources to train ML models, conduct real-time analytics, and manage virtual lab environments. While there are scalable options in a cloud-based design, institutions must weigh the costs in terms of network reliability as well as technical expertise for system support and long-term use (Walia, 2024). The last successful adoption depends on compatibility with existing educational technologies, such as learning management systems (LMS) and student information systems (SIS). However, this level of integration often depends on open data standards and interoperable APIs (Application Programming Interface) to enable seamless data sharing and a unified user experience (Stanhope & Rectanus, 2016).

Additionally, interdisciplinary collaboration should be encouraged for the development and evaluation of adaptive AI systems in engineering education. Good design is an artificial intelligence expert collaborating with learning scientists and programmers who know how educational systems work. Besides its technical value, pilot studies with longitudinal data are needed to examine what is the effect of the platform for learning (in terms of outcomes and skills that were gained over time) and engagement in an applied context (Berisha Qehaja et al., 2025).

Lastly, institutional readiness is a key factor influencing the success of implementation activities. Involving a range of stakeholders such as students, faculty, leaders, and IT staff in co-design processes and pilots can facilitate matching the system's functions with institutional needs, decrease resistance to adoption, and increase relevance (Luckin & Holmes, 2016). Policy Benchmarking Results suggest the need for an institutional-level analysis of academic integrity infrastructure, a re-evaluation of measures that represent course workload models identified to facilitate evidence-based teaching and faculty development, with a focus on this domain. Supporting such strong ethics oversight approaches around AI deployment in education, as exist, for example, in medical research, will be important to underpin transparent, just, and responsible practice (Williamson & Eynon, 2020).

Future Directions and Conclusion

AI-based adaptive online learning venues were identified as an emerging and important direction in the development of engineering education, especially when facing increasing demands for individuality, expanded scale, and skill-relevant learning. The study has characterized the current state of pedagogy in engineering education and designed a conceptual framework that combines learning analytics, adaptive content delivery, intelligent tutoring systems, virtual labs, and personalized assessment to address the special pedagogical requirements of engineering education. By placing these in a cycle of data-informed feedback

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loops, the model constituted an improvement over current AIED research in terms of the cognitive, experiential, and application aspects of learning.

Theoretical in nature, it is recommended that future research empirically investigate the proposed framework through longitudinal studies across different engineering domains. These can explore how intelligent AI platforms may be applied to learning efficacy, retention rates, competency levels achieved, and learning mode implications among students. Likewise, subsequent longitudinal models could allow for direct comparisons between more broadly defined institutional types (e.g., research-intensive universities vs. community/teaching-based colleges) to test the stability and generalizability of the model.

High-level AIs may also be included in the future AI-engineering education ecosystems. New tools in the future may use new approaches, such as deep reinforcement learning (DRL) to make field applications more likely. On the other hand, one can use generative AI to develop immersive learning experiences that deliver dynamic instruction, exposing learners to content. However, now that engineering is being taught in an interdisciplinary manner, one can learn more about how adaptive AI supports learning in other disciplines as well, such as data science, sustainability, or user experience design.

It has also failed to move forward on other fronts, including web services interoperability and standardization. Open standards for metadata representation, data exchange, and system integration are essential to enable the deployment of AI platforms that align with institutional and learning contexts. Simultaneously, research on the best possible human-AI partnerships needs to be conducted to ensure that intelligent tutoring systems augment rather than negate educators' pedagogical insights. Human judgment and guidance, as well as ethical accountability, also need to be built into AI-embodied learning spaces.

Ethical guidance on the responsible use of adaptive AI for engineering education must be developed and supported by ongoing investment. What we need in the future is an openness, trustworthiness, and ethical framework for data, which includes privacy, accountability, explainability, and liability. This could include responsible stewardship, professional development for teachers, and inclusivity-by-design to make sure AI innovation in this field is sustainable -pun intended- as teaching engineering can both scale up and down.

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