

A Pedagogical Framework for Project Management in AI-Driven Engineering Design

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Abstract: Traditional engineering design pedagogy, built on linear, phase-gated project management models, is increasingly insufficient for preparing students for modern AI-driven design projects. This new paradigm presents a dual pedagogical challenge: 1) a process challenge, as AI projects are defined by iterative, data-dependent, and uncertain lifecycles, and 2) a social challenge, as AI shifts the engineer's role from "doer" to "orchestrator" within a complex human-AI collaboration. This paper presents an integrated 10-unit curriculum development from an Erasmus+ EU project, as a novel pedagogical solution. The framework is designed to scaffold process uncertainty, systematically bridging the gap between traditional project management and the unique, iterative lifecycles of AI projects. This scaffold then enables the teaching of new, human-centric collaborative competencies through active learning interventions, which are grounded in practice-based learning principles. These include stakeholder co-design simulations and a role-playing exercise where students must navigate the inherent conflicts between AI performance and human-centred design goals.

Keywords: Artificial intelligence (AI), Design Education, Triangle of Shared Responsibility, Project-based learning, project management

1 Introduction

For decades, engineering design education has been anchored in traditional project management principles, characterised by linear, phase-gated structures (Shekar, 2014). In practice, design and project management are deeply interlinked; design is typically conducted within project structures that require resource control and decision-making (Ulrich et al., 2020). However, as Artificial Intelligence (AI) is rapidly getting integrated into the engineering design process, it is expected that supporting fields such as project management will also see a rapid shift (Garcia-Holgado et al., 2025). This new paradigm introduces a fundamental process challenge for pedagogy. Unlike their traditional counterparts, AI projects are defined by iterative model development cycles, heavy dependence on data quality, continuous refinement, and inherent uncertainty (De Silva & Alahakoon, 2022; Rad, 2025). This creates a significant pedagogical gap, as the predictable, linear frameworks traditionally taught no longer map to the evolving realities of practice (Verganti et al., 2020). Recent discussions in design education conferences have focused on generative AI and the exploration of human-centred AI integration (Brisco et al., 2025; Georgiev et al., 2025), further highlighting the need for updated curricula. On one hand is the acknowledgement of engineering design as an inherently complex sociotechnical process, which is deeply rooted in real-world application, on the other hand is the importance of preparing students for uncertainty and risk which is developing with new practice paradigms. Further, while much emphasis is focused on AI in design, the role of AI in design education deserves special attention. This paper therefore argues that AI is not just a tool for design, but also a powerful enabler of learning, closely tied to how we acquire knowledge and how we engage with design in practice.

Furthermore, this process shift introduces a second challenge. AI is not merely a new tool; it is a new actor in the design process. This shift necessitates a new foundational model for curriculum design: the *Triangle of Design Responsibility* (Pradas Gomez et al., 2025; Pradas Gomez et al., 2024), which conceptualises design as a distributed activity among three agents, i.e., human designers, traditional engineering tools, and generative AI systems. This model reframes engineering education to prepare students for orchestrating design tasks across these agents, rather than merely executing them. Current design curricula are limited in addressing this challenge, teaching AI as a technical tool without providing a framework for managing its inherent uncertainty or its social impact. The development of the course discussed in the paper was motivated by this gap, aiming to integrate generative AI into product design education by addressing both the technical and socio-ethical dimensions. Particular focus is on the project management aspect of the design process. This leads to the central research question addressed in this paper:

RQ: *How can engineering design education effectively prepare students to manage the unique uncertainties introduced by AI-driven design project workflows?*

This paper presents the "Project Management and Real-World Applications" module as a novel, 10-unit pedagogical framework that employs the triangle of shared responsibility (Pradas Gomez et al., 2025) as a new foundational element for curriculum development, designed to explicitly address this challenge while drawing upon established pedagogical principles like constructive alignment (Biggs, 1996) and practice-based learning (Shekar, 2014).

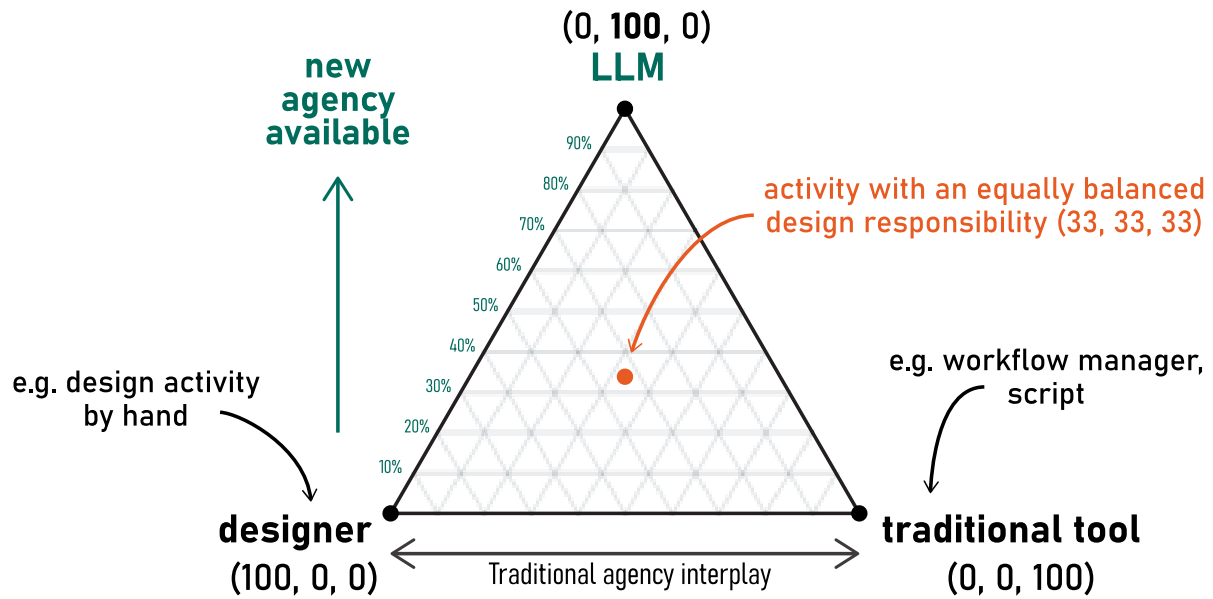


Figure 1 Triangle of shared responsibility as proposed by (Pradas Gomez et al., 2025). Reproduced with permission.

2 Background

In this section, we discuss relevant topics, existing curriculum models, and a few foundational concepts as a basis for the pedagogical framework presented later. While the focus of this paper is on education, the motivation stems from changes in engineering practice driven by the introduction of AI.

2.1 Pedagogical Frameworks in Engineering Design Education

Curriculum development in engineering has historically drawn on established frameworks such as constructive alignment (Biggs, 1996), where the aim is to first define learning outcomes, followed by aligned assessments and activities. Rooted in the ideas of constructivism, constructive alignment has been widely used in engineering education to ensure that the teaching methods, assessments and learning activities are coupled tightly to the Intended Learning Outcomes (ILOs) (Malmqvist et al., 2011). A number of approaches take the idea forward along with a number of active learning strategies, including Problem-based learning (PBL), project-based learning (PjBL) and challenge-based learning, which emerged from PBL and Conceive-Design-Implement-Operate (CDIO) approaches (Kohn Rådberg et al., 2020). Originating in medical education in the 1960s, PBL was adapted to engineering as a student-centred pedagogy that begins with an ill-structured, real-world problem (Noordin et al., 2011). Students typically work in teams to identify the problem, research solutions and propose answers, with teachers guiding them rather than directing the process. PjBL, which shares its roots with PBL, focuses on the creation of a tangible product or a system through a structured, long-term project. PjBL typically includes defined deliverables (e.g., prototypes, reports, or simulations) and integrates technical, project management, and teamwork skills (Shekar, 2014). The CDIO framework extends these pedagogical approaches into a comprehensive curriculum model that is specifically modelled for and from a typical engineering lifecycle (Crawley et al., 2011; Crawley et al., 2007). CDIO explicitly structures education around conceiving ideas, designing solutions, implementing systems, and operating them in context. Further, it argues for embedding personal, interpersonal, and system-building skills alongside technical knowledge. It operationalises constructive alignment at the program level by defining graduated ILOs across the CDIO phases, aligning them with project-based teaching and learning activities, and using authentic assessments such as peer reviews, stakeholder presentations, and operational testing (Edström & Kolmos, 2014).

Beyond constructive alignment and project-based pedagogies, contemporary engineering education increasingly frames learning as a scaffolded process in which complexity, responsibility, and autonomy are gradually introduced to learners. Scaffolding theory emphasises structuring learning activities so that students are supported in navigating uncertainty while progressively developing independent judgment. In design education, this perspective aligns with views of design not only as an outcome-oriented process but as a learning scaffold through which students engage with ambiguity, iteration, and socio-technical complexity. In this sense, the design process itself becomes a pedagogical structure that supports learning rather than merely a pathway to a solution.

A recurring challenge noted in engineering education is that students often confuse the CDIO framework with traditional product development processes, likely because both follow structured, phase-based models. However, while product development processes are primarily focused on delivering engineered products, CDIO is fundamentally a pedagogical framework designed to support learning through real-world, complex challenges. This is also evidence that the design

process is not just about creating solutions, but can also be used as a scaffold for the learning process. Through the scaffolding of design students engage in exploration, reduce uncertainty, and develop deeper insights into how systems work. This reinforces the idea that learning processes and design processes are not only parallel but deeply interrelated.

Recent adaptations of CDIO have addressed emerging technologies, including AI integration. For example, the Project-work Artificial Intelligence Integration Framework (PAIIF) builds on CDIO to use AI-based methods in real-world engineering projects (Nikolic et al., 2025). Further, a number of papers use AI as a pedagogical enhancer within CDIO's experiential framework (Lei et al., 2025) or as a specific teaching and learning task helper, such as in grading/assessment or rubric refinement (Nikolic et al., 2025). Despite these advances, CDIO and aligned active learning approaches often treat AI as a technical enhancement rather than a sociotechnical actor. This arguably puts a constraint on the potential to prepare students for the shared responsibility dynamics and collaborative uncertainties inherent in human-AI collaboration. This gap is addressed in this paper by using the Triangle of Shared Responsibility framework by Pradas Gomez et al. (2025), which is discussed next.

2.2 The Triangle of Shared Responsibility (TSR) in AI Systems

As Large Language Model (LLM) based systems have emerged, a number of researchers have explored their use in engineering design and project management. A number of studies frame AI as a tool that can be used, for example, in simulation, design optimisation, and communication and so on (see Khanolkar et al. (2023) for a review). However, a growing body of research argues that treating AI as a teammate (Seeber et al., 2020), may lead to better outcomes in design situations as AI systems, particularly generative and agentic models, exhibit behaviours that are traditionally associated with human team members. Frameworks such as the Human-AI Joint Cognitive Systems (HAJCS) by Xu and Gao (2024), emphasise joint performance and shared cognition between humans and AI. Similarly, the COLLEAGUE framework (Gervasio et al., 2025) proposes a mixed-initiative collaboration, allowing AI to have a shifting role within design teams. Finally, specifically for the context of engineering design, Pradas Gomez et al. (2025) propose the "triangle of shared responsibility", which delineates accountability among stakeholders. This model frames responsibilities in a triangular structure involving the three actors, i.e., the AI systems, the user and the existing traditional tools used in engineering design. In this framework, engineers orchestrate interactions between human expertise, traditional tools, and AI agents, instead of using AI as a tool, similar to traditional tools.

In educational settings, this translates into learning by co-designing with AI. The Triangle of Shared Responsibility (TSR) builds directly on this pedagogical idea. This structure makes explicit the interdependencies, communication flows, and accountability boundaries that students must navigate in AI-driven engineering design.

2.3 Identified Gaps and Implications for Curriculum Development

The reviewed frameworks and pedagogical models highlight a growing recognition of AI, especially LLM-based methods and tools as a collaborative actor in engineering design, and not merely a tool which can be used in different tasks. However, current curriculum structures do not account for these conceptual shifts. While CDIO and other active learning strategies provide a basis, so far, no pedagogical development considers human-AI teaming, especially in the context of engineering design and associated project management. Further, emerging literature explores AI as an educational tool (e.g., Byrne et al. (2025); Gong et al. (2025); Rodriguez-Ferradas et al. (2025)), specific pedagogical developments addressing human-AI teaming in engineering design and project management remain limited. This gap presents an opportunity to rethink engineering education, not just in terms of content, but in how students engage with AI systems as co-designers and decision-makers, especially in engineering design and project management.

An important pedagogical consideration is the evolving expectation among students for rapid feedback. CDIO was originally designed to expose students to real-world, complex challenges while aligning with specific learning objectives. A key strength of CDIO lies in its emphasis on blending technical and interpersonal skills with the specific learning objectives. In this context, generative AI tools offer a new layer of interactivity, enabling students to engage in faster experimentation and receive immediate feedback. However, this also necessitates a renewed focus on critical reflection, especially when students interact with AI-generated outputs (Walter, 2024). Further, any pedagogical development must also consider the sociotechnical complexities, where scaffolding can help students navigate and use AI uncertainties to their advantage.

To address this, the next section introduces a pedagogical framework that integrates the Triangle of Shared Responsibility with active learning principles. It is built on the concept of Human-AI teaming, as discussed in previous sections. The next section presents a 10-unit module that uses the triangle within a constructively aligned framework to scaffold both procedural uncertainties and pedagogical interventions which are needed for AI-driven engineering design projects.

3 Structuring Learning within the Triangle of Shared Responsibility

As artificial intelligence, especially LLMs, becomes increasingly integrated into engineering design and project management, it introduces three types of uncertainty: technical, pedagogical, and tool-based. The technical challenges primarily arise from the uncertainties AI brings to the design process, including, but not limited to, uncertainties related to data quality and bias (Rad, 2025), model transparency and interpretability of outputs, and so on. The pedagogical uncertainties arise from how pedagogical interventions are applied in traditional engineering courses vs courses where AI acts as a collaborator (designer, project manager) along with the students. A third layer of uncertainty emerges from the coexistence and integration of legacy tools and conventional engineering methods into AI-driven design workflows.

This course was designed in response to the three uncertainties outlined above. At its core lies the Triangle of Shared Responsibility, Pradas Gomez et al. (2025), which positions three actors at the vertices of a triangle: the human designer or project manager, the AI system, and the traditional engineering tools and codes. The space within the triangle is not static but a dynamic space where the responsibility of the three actors is negotiated, shared and contested. Although the TSR was originally developed within the context of engineering design practice, its pedagogical relevance to education lies in how it mirrors the shifting roles and interactions within learning environments for AI-driven design projects.

Building on the Triangle of Shared Responsibility, each module is carefully composed to maintain a balance across three dimensions: the type of AI-related uncertainty addressed, the integration of existing engineering methods and tools, and the nature of the teaching and learning interventions. The aim is not to balance these three dimensions within every individual unit, but to purposefully allow asymmetry so that each unit can emphasise a particular vertex or edge of the triangle. This ensures that students experience AI as a co-actor rather than a static tool, with its role shifting across contexts. However, when seen collectively, these asymmetries are sequenced to achieve an overall balance within the triangle. Figure 2 illustrates this principle: each module is conceptualised as a hexagonal learning unit. Unlike the TSR, the hexagonal shape does not have intrinsic meaning. Each module is influenced by three directional vectors: uncertainty, tools, and pedagogy, whose relative magnitudes determine its position within the triangle.

3.1 Module-level asymmetry

Table 1 provides a qualitative overview of how each module is positioned within the Triangle of Shared Responsibility. It shows each module's lean within the triangle and how the three forces: AI-Induced Uncertainty, Tool Integration, and Pedagogical Intervention, influence the lean. In Figure 2, tool integration and Pedagogical interventions are called "Existing methods and tools" and Teaching and Learning Activities (TLAs), respectively. This mapping illustrates the asymmetry at the unit level and overall balance across the sequence.

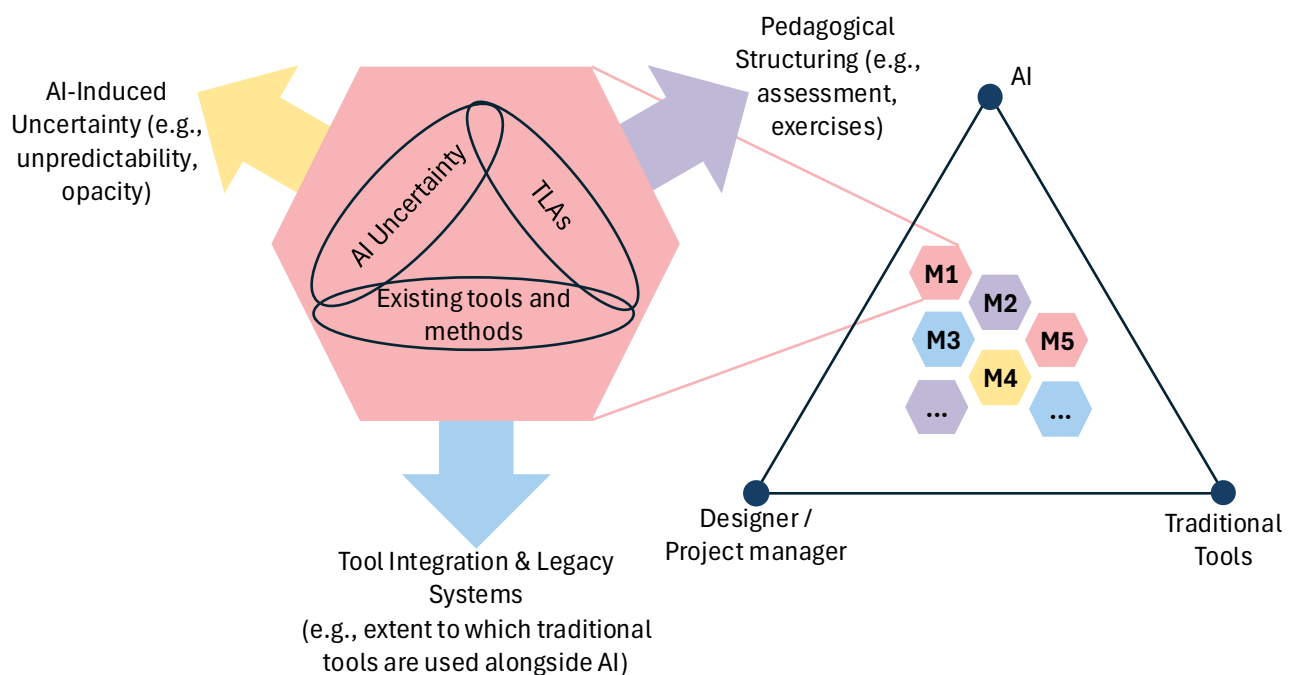


Figure 2 Principle of individual module design in the context of the triangle of shared responsibility, and the position of all the modules collectively within the triangle.

Table 1 Module positioning within the Triangle of Shared Responsibility, showing dominant vertex and influence of AI-Induced Uncertainty, Tool Integration, and Pedagogical Intervention.

Unit	Dominant Vertex	AI-Induced Uncertainty	Tool Integration	Pedagogical Intervention	Why this unit leans here
1 Intro to PM in AI Design	Human–AI	High: Students face ambiguity in planning iterative AI lifecycles.	Moderate: Comparison with traditional PM and risk analysis tools.	Moderate: Lecture supported by forum-based reflection and case analysis.	Focuses on planning under uncertainty.
2 Real-world AI Project Lifecycle	Human–AI	High: Lifecycle unpredictability and dynamic checkpoints.	Moderate: Integration with CAD/PLM tools.	Moderate: Case-based walkthrough plus forum observations.	Builds skills for managing unpredictable AI lifecycles.
3 Stakeholder Engagement & Co-Design	Human–Tool	Low: AI uncertainty is peripheral.	Moderate: Co-design tools and AI for stakeholder analysis.	High: Role-play, ethical reflection, and forum discussions simulating stakeholder engagement.	Emphasises collaboration and stakeholder dialogue.
4 Risk Management in AI Design	AI–Tool	Moderate: Reframing risk frameworks for AI.	High: FMEA, HAZOP, Fault Tree Analysis with AI.	Moderate: Structured analysis tasks plus applied FMEA exercise and discussion.	Focuses on technical assurance and compliance.
5 Resource Allocation & Budgeting	AI–Tool	Low: Predictability of cost models.	High: Integration of GenAI cost estimators with legacy financial tools.	Moderate: Planning exercises using GenAI cost estimators and collaborative budgeting tasks.	Centres on cost and resource planning with AI tools.
6 Collaborative Work in AI Teams	Human–Tool	Moderate: AI as teammate introduces some uncertainty.	Low: Minimal technical integration focus.	High: Role-play, conflict resolution simulation, and reflective writing.	Develops teamwork and conflict resolution skills.
7 Case Study Analysis	Centre (Balanced)	Moderate: Transferability of AI practices.	Moderate: Use of mapping tools and frameworks.	Moderate: Team-based case mapping and pitch presentations using a collaborative wiki.	Synthesises lessons from previous units.
8 Ethics & Responsibility	Human–Tool	Low: AI uncertainty is secondary.	Moderate: Audit tools and compliance frameworks.	High: Debate, scenario analysis, and creation of an ethics applicability matrix.	Strengthens ethical reasoning and accountability.
9 Adapting AI Strategies	Centre (Balanced)	High: Technique selection under domain constraints.	High: Mapping AI methods to legacy workflows.	High: Wiki-based mapping of AI techniques and justification tasks.	Prepares students for strategic AI adaptation.
10 Capstone Project	Centre (Balanced)	High: Real-world implementation uncertainty.	High: Full-stack integration of AI and legacy tools.	High: Project-based learning with integrated reflection and presentation.	Combines all skills in a real-world project.

Rather than forcing symmetry inside each unit, we design purposeful asymmetry so that one force leads and the other two play supporting roles. When AI-Induced Uncertainty leads, the unit leans toward the human–AI edge and focuses on helping students interpret uncertainty, coordinate AI-driven tasks, and gather evidence when decisions are unclear (see Table 1, Modules 1 and 2, where students plan iterative lifecycles, define AI-specific milestones, and interrogate model limits. When Tool Integration leads, the unit leans toward the AI–tool edge and centres technical assurance: students, for example, use AI outputs inside established tools such as requirements matrices, FMEA/FTA/HAZOP etc., as in Units 4 and 5. When Pedagogical Intervention leads, the unit leans toward the human–tool edge and centres human agency, collaboration, and accountability (e.g., stakeholder co-design and structured conflict resolution in Units 3 and 6, and ethics and responsibility in Unit 8). In each case, the supporting forces remain present (e.g., even in a Tool-Integration-led unit, students still confront uncertainty and engage in guided reflection), but the instructional design clearly shows which skill is most important.

3.2 Collective symmetry of modules

Collectively, the modules are arranged to guide shifts in responsibility across the Triangle of Shared Responsibility. This sequencing is made to ensure students repeatedly experience transitions between human judgment, AI assistance, and tool-based assurance. The early units (Modules 1 and 2) focus on human–AI interaction to build confidence in planning under uncertainty. The students plan under uncertainty and set AI-specific milestones (e.g., lifecycle mapping and milestone planning). The sequence then moves toward AI–tool integration (Modules 4 and 5), where students learn to validate AI outputs using established codes, models, and economic frameworks, such as FMEA/FTA/HAZOP. Later, the emphasis returns to human–tool collaboration (Modules 6, 8) to strengthen skills in teamwork, stakeholder engagement, and ethical decision-making when AI acts as a collaborator rather than a passive tool. For example, structured stakeholder role-plays in Module 3, team conflict resolution around accuracy vs. usability in Module 6, and ethics applicability matrices in Module 8. Two re-centring nodes ensure integration across all three forces: Module 7 synthesises lessons through case mapping and pitches, and Module 9 focuses on adapting AI strategies to different design challenges. In this module, students map AI techniques such as CNNs, GANs, and reinforcement learning to domain-specific problems, justifying their choices based on data type and project goals. Finally, Module 10 brings these strands together in a real-world project where students apply AI methods alongside legacy tools and teamwork practices to deliver a complete solution.

3.3 Pedagogical Uncertainty as a Driver of Module in TSR

Pedagogical uncertainty is the third uncertainty type, which is used to shape how learning is situated within the Triangle of Shared Responsibility (TSR). In our case, we use targeted interventions to reposition a module toward the Human–AI, AI–Tool, or Human–Tool edges. We argue that pedagogical uncertainties arise not only from how we teach, but from what it means to teach when AI itself becomes an actor in the learning process. This uncertainty is twofold. First, it stems from the shifting pedagogical boundaries where AI is no longer a passive tool but an active collaborator, in the case of engineering design and project management, sometimes a designer, sometimes a project manager, and at times a decision-maker. Second, it emerges from the challenge of designing teaching and assessment strategies that can accommodate and even make use of this shifting capability. In this course, pedagogical uncertainty is not treated as a problem to be resolved, but as a design condition to be used to position modules within the triangle of shared responsibility.

We approach this through constructive alignment (Biggs, 1996), using teaching and learning activities such as assessment, to support learning outcomes and also to enable AI to function as an orchestrator within the learning environment. In practice, this means designing interventions that help students actively navigate the uncertainties around roles and agency, for example, who does what: human, AI, or legacy tools. Further, it becomes an enabler in clarifying process logic; what constitutes a valid design process when AI is probabilistic and iterative. The aim is therefore not to eliminate these uncertainties by intentionally using them to scaffold the learning process. In this way, pedagogy is used as a lever that not only supports constructive alignment but also enables students to engage with AI as an evolving actor within the learning environment, thereby shaping how each module is positioned within the Triangle of Shared Responsibility. This uses scaffolding to intentionally use uncertainties as learning opportunities, aligning with modern views of supporting learners in achieving complex outcomes (Crismond, 2011).

We use three types of interventions to influence the pedagogical uncertainty, each shifting the module toward a different TSR edge:

- **Orchestrative interventions** are used when the goal is to surface uncertainty and develop students' capacity to plan and adapt in the presence of AI's probabilistic and iterative nature. In Modules 1 and 2, for example, students engage in lecture-supported forum reflections and case-based walkthroughs that require them to define AI-specific milestones, anticipate model unpredictability, and justify checkpoints. These activities increase uncertainty around process logic and decision-making and therefore reposition the module toward the Human–AI edge of the triangle.
- **Assurance interventions** are used to reduce uncertainty, particularly around evidence standards and compliance. This is done by anchoring learning in structured, often pre-existing and established legacy tools and methods.

Modules 4 and 5 exemplify this approach through tasks such as FMEA completion, risk prioritisation discussions, and collaborative budgeting using GenAI estimators. These activities help students translate AI outputs into established engineering formats, binding them to legacy tools and codes. As a result, the module shifts toward the AI–Tool edge.

- **Deliberative interventions**, on the other hand, reframe uncertainty as a space for ethical and collaborative negotiations. In Modules 3, 6, and 8, students participate in role-play, conflict resolution simulations, and scenario-based ethical debates. These interventions aim to bring out questions of accountability, stakeholder engagement, and value alignment, encouraging students to think about the social dimensions of AI in design. The effect is a repositioning toward the Human–Tool edge, where human judgment and ethical reasoning are central to the decision-making and project management process.

There are a few balanced modules, such as 7, 9, and 10, that combine these interventions to recouple the edges. Module 7 integrates orchestrative and deliberative strategies through team mapping and pitch presentations. Module 9 couples exploration to assurance via wiki-based technique mapping, while the final project in Module 10 synthesises all three interventions in a real-world design scenario, requiring the students to apply all the knowledge in a consolidated and holistic manner.

This framing positions pedagogical uncertainty as a deliberate module design variable rather than a post-facto outcome. By controlling its various dimensions, educators can actively shape how students experience responsibility distribution across the TSR. This in turn ensures that learning replicates to the extent possible, the socio-technical complexity of AI-driven design projects.

4 Discussion

The integration of AI into engineering design education requires that we not only look at new tools but also rethink the existing pedagogical instruments. As AI becomes more and more pervasive in the design work, it simultaneously challenges the educational structures that prepare students for such work. This paper has argued that engineering design and project management, often treated as an essential skill in engineering education, must now be repositioned as a central pedagogical concern. In AI-driven design contexts, managing uncertainty, orchestrating collaboration, and aligning technical and ethical considerations must be treated as core competencies.

The framework presented here addresses this shift by integrating project management within a pedagogical structure that reflects the realities of AI-driven engineering design practice. Based on the Triangle of Shared Responsibility (TSR), the course design explicitly acknowledges the distributed nature of responsibility in modern design teams, where humans, AI systems, and traditional tools must interact. We posit that through this model, we can enable the consideration of both the sociotechnical complexity of engineering but can also provide a scaffold for teaching students how to navigate and use it to their advantage.

Importantly, the framework aligns with existing and established frameworks such as CDIO. For example, the framework aligns with CDIO's emphasis on real-world challenges, iterative learning, and the integration of technical and interpersonal skills. However, it also addresses a critical gap: while CDIO and similar models have traditionally treated AI as a technical enhancement, this framework positions AI as a pedagogical actor. Generative AI, in particular, introduces new forms of interactivity in learning. Students can now receive rapid feedback, iterate on ideas in real time, and explore design alternatives at unprecedented speed. This aligns with evolving expectations for more responsive and engaging learning environments. The framework enables this by providing a balancing perspective.

At the same time, this also introduces a pedagogical risk: the potential reduction of cognitive effort. As AI systems become more capable, there is a danger that students may rely on them to generate solutions without engaging in the critical reflection and creative exploration that are foundational to design thinking. Design is not merely about producing outputs, it is about learning through doing, questioning assumptions, and iteratively refining ideas. The framework addresses these concerns by embedding orchestrative, assurance, and deliberative interventions that focus on uncertainty, require justification, and encourages ethical reasoning, both at the course design level and at the implementation level. However, this raises two critical questions for educators: How do we preserve cognitive engagement when AI accelerates tasks? And how do we measure learning when outputs can be generated instantly? Our framework addresses these by the use of the three aforementioned interventions that require justification, reflection, and ethical negotiation.

The framework, therefore, does not encourage the treatment of AI as a source of answers, but as a helper for deeper learning. It uses the strengths of the technology, speed, pattern recognition, and generative capacity, while also ensuring that students remain active in the design and learning process. Future research should explore assessment strategies that capture these deeper cognitive processes, rather than focusing solely on deliverables.

The framework presented in this paper has several limitations. First, the framework is conceptual and design-oriented and does not yet include empirical evidence from classroom implementation or learning outcome assessment. Second, the

curriculum was developed within the context of a European engineering education project, which may limit its direct transferability to other institutional or cultural settings. Third, the framework assumes a baseline level of student familiarity with engineering design and project-based learning and may require adaptation for earlier stages of engineering education. Work is already ongoing on focusing on piloting the framework in live courses. The pilot study aims to collect student reflections and performance data which will lead to refining the module design based on observed learning challenges. Further research is also needed to investigate assessment strategies that can meaningfully evaluate learning when AI systems contribute substantially to design outputs. While the framework has not yet undergone large-scale classroom evaluation, several of its design choices are grounded in established pedagogical principles such as constructive alignment, practice-based learning, and scaffolded exposure to uncertainty (Biggs, 1996; Edström & Kolmos, 2014; Shekar, 2014). Ongoing and future work will focus on empirical validation through pilot implementations, student feedback, and reflective assessments to examine how effectively the framework supports students in managing uncertainty and human–AI collaboration in design projects.

5 Conclusion

This paper has introduced a pedagogical framework that integrates project management into AI-driven engineering design education, using the Triangle of Shared Responsibility (Pradas Gomez et al., 2025) as its foundation. By aligning with principles like constructive alignment and CDIO, the framework addresses the growing need to prepare students for the uncertainties of AI-driven design. Developed through the Erasmus+ DETAILLS project, the 10-unit module positions AI not just as a tool, but as a pedagogical actor that rethinks how students learn and collaborate. The framework's use of orchestrative, assurance, and deliberative interventions ensures that students engage critically with AI, rather than relying on it passively like with a tool. While validation is ongoing, early implementations suggest that careful integration into existing curricula is essential to maintain alignment with institutional structures. Nonetheless, the urgency to adapt is clear. As AI continues to make rapid changes to engineering practice, education must also evolve in parallel to help students with the skills, judgment, and ethical awareness needed for future design challenges.

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