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Integrating Generative AI in Engineering Education: Interaction Dynamics and Pedagogical Implications

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Abstract

Generative Artificial Intelligence (AI) is rapidly transforming engineering education, particularly in activities involving product representation and conceptual design. While existing literature has extensively addressed students' perceptions and the technical capabilities of AI systems, comparatively less attention has been devoted to the interaction processes that emerge during real educational tasks. This paper adopts a conceptual and educational perspective to examine how students interact with AI tools in design-oriented contexts. Building on insights from Human-Computer Interaction and design cognition, the study identifies recurring interaction tendencies and analyzes them through key dimensions such as goal formulation, interpretation of outputs, and distribution of agency between user and system. Rather than proposing a formal framework, the paper develops an extended conceptual discussion aimed at supporting pedagogical reflection, and outlines implications for teaching practices that promote reflective engagement and meaningful learning.

Keywords

Generative AI, Engineering Education, Human-AI Interaction, Product Representation, Agency, Design Cognition

1. Introduction

The rapid diffusion of generative Artificial Intelligence (AI) is reshaping educational practices across disciplines, with particularly significant implications for engineering education. Tools capable of producing textual, visual, and conceptual representations have become increasingly accessible, enabling new forms of interaction with design problems. Activities traditionally centered on manual construction of representations—sketching, modeling, and conceptual description—are now progressively mediated by AI systems that generate and transform representations in real time.

This transformation raises fundamental questions about learning in design-oriented settings. While generative AI offers clear advantages in terms of efficiency and access to alternative solutions, its integration cannot be reduced to a simple enhancement of existing tools. It introduces a qualitative shift in how students engage with representations, structure their reasoning, and distribute cognitive effort between themselves and external systems. Understanding the role of AI in engineering education, therefore, requires moving beyond a tool-centered perspective toward an interaction-centered approach.

A substantial body of research has examined the role of AI in education, highlighting both the opportunities—increased productivity, support for ideation, expanded solution spaces—and the risks: overreliance, reduced critical engagement, and difficulties in interpreting system outputs [1] [2]. Research on AI literacy has emphasized the importance of developing competencies for effective and responsible use [3]. However, relatively limited attention has been devoted to the actual dynamics of interaction that emerge when students engage with AI during complex cognitive tasks.

From a Human-Computer Interaction (HCI) perspective, interaction with AI systems involves the construction of mental models, interpretation of system behavior, and ongoing calibration of control between human and machine [4] [5]. In design-oriented tasks, this interaction is further mediated by external representations, which play a central role in supporting reasoning and reflection. Classic studies in design cognition have shown that representations function as active cognitive artifacts enabling iterative cycles of interpretation and reformulation [6]-[8].

The introduction of generative AI into this context fundamentally alters the designer-representation relationship. Rather than constructing representations incrementally, students are often presented with complete outputs generated by the system. The emphasis shifts from production to interpretation, from manual construction to selective evaluation, from direct control to negotiated interaction. As a result, the design process becomes a dialogue between human intention and machine-generated proposals, in which the boundaries of agency are continuously redefined.

In practice, students do not adopt a uniform approach when using AI tools. Different modes of interaction emerge, reflecting variations in how students formulate goals, interpret outputs, and engage in iterative processes. Rather than treating these differences as mere variations in attitude, it is useful to interpret them as distinct interaction tendencies reflecting different ways of organizing the relationship between intention, action, and evaluation. These tendencies are dynamic patterns that can evolve over time and vary across contexts, yet their recurrence suggests they capture meaningful aspects of student engagement with AI.

Building on these considerations, this paper adopts a conceptual perspective aimed at analyzing interaction dynamics in AI-supported product representation tasks. The objective is not to propose a formal or prescriptive framework, but to develop a structured interpretation of recurring interaction tendencies and their underlying dimensions—goal formulation, interpretation of AI-generated outputs, and distribution of agency—and to use these as a basis for discussing pedagogical implications. It should be noted that the tendencies and dimensions proposed are conceptual constructs developed through interpretive analysis; they are not empirically validated types and should be understood as analytical tools for pedagogical reflection rather than descriptive categories.

2. Related Work

2.1. Conceptual Approach

The conceptual approach underlying this paper draws on a selective review of literature across three intersecting fields: AI in education, Human-AI interaction, and design cognition. Sources were identified through targeted searches in academic databases, prioritizing contributions that address interaction processes, representational practices, and pedagogical implications of AI use. The proposed interaction tendencies and analytical dimensions were developed inductively, informed by recurring observations in engineering education contexts involving AI-supported design activities. These observations, while not constituting a formal empirical study, provided the interpretive grounding from which the conceptual constructs presented in the following sections were derived.

2.2. Literature Review

Research on AI integration in education has expanded significantly, reflecting both the increasing availability of AI systems and their growing influence on learning environments. Early contributions focused on intelligent tutoring systems and adaptive learning platforms, grounded in well-defined pedagogical models emphasizing measurable outcomes. The emergence of generative AI has introduced a different paradigm: systems capable of producing open-ended outputs, including text, images, and design concepts.

This shift has prompted renewed interest in AI not only as an instructional tool but as a cognitive partner supporting creative and exploratory tasks. Studies have consistently highlighted a dual perspective: on one hand, AI is associated with enhanced efficiency and expanded access to information; on the other, concerns arise regarding overreliance, superficial engagement, and the potential erosion of critical thinking [1] [2]. AI literacy has emerged as a key concept, referring to competencies required to effectively and responsibly interact with AI systems [3], yet these often remain at a general level without addressing how they are enacted during specific tasks.

The field of Human-AI interaction has provided valuable insights into user engagement with AI systems. Amershi *et al.* [4] emphasize transparency, feedback, and controllability as essential design principles, highlighting that effective interaction requires users to develop an understanding of system capabilities and limitations [9]. Shneiderman [5] advocates for human-centered AI in which systems augment rather than replace human capabilities. However, much of this research has focused on decision support and machine learning interpretability, with limited attention to design-oriented tasks where representational processes play a central role.

Design cognition research offers a complementary perspective. Representations—sketches, diagrams, models—are not merely communication tools but active components of cognitive processes [6] [8]. Schön's [7] reflection-in-action describes design as a continuous dialogue between the designer and the situation, in which each action generates new insights informing subsequent decisions. The introduction of generative AI adds a new actor to this interaction loop, shifting part of the representational process from the human to the system and raising important questions about how cognitive processes are distributed and how this distribution affects learning [10].

Despite these contributions, the intersection of generative AI, representational processes, and educational interaction remains underexplored. Existing studies tend to address these aspects separately. This paper contributes to bridging this gap by adopting an interaction-oriented perspective that integrates insights from AI in education, Human-AI interaction, and design cognition, examining how interaction dynamics emerge during AI-supported design tasks and how they can inform pedagogical approaches.

3. AI in Product Representation Tasks

Product representation constitutes a central component of engineering design, playing a fundamental role in both communication and cognition. Through sketches, diagrams, and models, designers externalize ideas, explore alternatives, and progressively refine their understanding of the problem space. These tasks include, for example, producing freehand sketches of mechanical components, generating conceptual layouts of product architectures, creating annotated diagrams for system-level design decisions, and developing preliminary 3D models of product concepts. In educational contexts, these activities are not merely instrumental but form an essential part of learning, enabling students to engage in iterative reasoning and to develop design competence through practice.

Traditionally, the construction of representations has been a gradual and effortful process, with each representation acting as both a product and a stimulus for further reasoning. The introduction of generative AI significantly alters this dynamic: students can now access complete or partially complete outputs generated by the system. The representational process becomes a collaborative activity involving both human input and machine-generated contributions.

This shift has important implications for student engagement. The balance between production and interpretation changes: while traditional approaches emphasize creating representations, AI-mediated processes place greater emphasis on evaluating, selecting, and adapting generated outputs. Students must interpret representations they did not directly construct, assess their relevance, and decide how to integrate them into their design process—a layer of cognitive activity closely linked to judgment and decision-making.

The availability of AI-generated alternatives also expands the design space, enabling rapid generation of multiple concept variations. This can support creative exploration and reduce the effort required for initial ideation. However, it also raises the risk of excessive reliance on generated outputs and a more passive role in the design process. The speed of AI generation further reduces temporal constraints that traditionally enforced reflection: outputs are produced almost instantaneously, potentially leading to shallow interaction patterns where students move quickly between alternatives without deeper analysis.

From a pedagogical perspective, AI affects not only the efficiency of task execution but also the nature of cognitive engagement. It influences how students formulate design intentions, interpret outcomes, and navigate the iterative process. The system shapes the representational environment, introducing possibilities and constraints that influence student behavior. The design process becomes a form of mediated interaction in which the student continuously negotiates meaning and direction with AI-generated outputs—a dynamic requiring careful consideration in educational settings where the goal is not only to produce outcomes, but to support learning.

Table 1. Recurring interaction tendencies in AI-supported engineering design tasks: key characteristics and educational implications.

Interaction Tendency	Key Characteristics	Educational Implications
Exploratory	Frequent prompt reformulation; generation of multiple alternatives; active comparison of outputs	Supports deeper cognitive engagement and reflection; risk of cognitive overload
Efficiency-oriented	Brief and focused interaction; minimal iteration; acceptance of first satisfactory output	Rational under time pressure; may limit learning opportunities if dominant
Cautious	Sporadic or selective AI use; alternation between AI and traditional approaches	May reflect critical stance; risk of underutilizing AI and limiting competency development

4. Interaction Tendencies

The integration of generative AI into design-oriented educational activities reveals that students do not engage with these systems in a uniform manner. Recurring patterns of interaction can be observed, reflecting different ways of organizing engagement with AI during task execution. These patterns are summarized in Table 1 and discussed in detail in the following paragraphs. These patterns—referred to here as interaction tendencies—are not fixed categories, but dynamic configurations that emerge from the interplay between individual characteristics, task requirements, and the affordances of the AI system. They should not be interpreted as student traits, stable strategies, or indicators of proficiency; rather, they are situational patterns that emerge in response to specific task conditions and contextual factors.

A first tendency can be described as exploratory interaction. Students exhibiting this mode treat AI as a resource for expanding the design space and supporting iterative reasoning. Their interaction is characterized by frequent reformulation of prompts, generation of multiple alternatives, and active comparison between outputs. Each AI-generated representation is not an endpoint, but a starting point for reinterpretation and refinement. From a cognitive perspective, this is associated with deeper engagement: students actively construct meaning through comparison, identifying patterns and opportunities for improvement. This behavior is consistent with reflection-in-action, where the designer continuously evaluates the consequences of actions and adjusts intentions accordingly [7]. However, the abundance of alternatives can lead to cognitive overload and excessive iteration without convergence.

A second tendency can be characterized as efficiency-oriented interaction. In this mode, students approach AI primarily as a tool for achieving predefined goals with minimal effort. Interaction is brief and focused: a prompt is formulated, an output is generated, and if deemed satisfactory, the process concludes with little further iteration. While this approach is rational given time and workload pressures, its educational implications are more complex. By limiting iteration and reducing engagement with the representational process, it may restrict opportunities for deeper learning. The issue arises when efficiency-oriented interaction becomes dominant, replacing rather than complementing more reflective forms of engagement.

A third tendency can be described as cautious interaction. Students exhibiting this behavior limit their engagement with AI systems, either due to lack of trust in outputs or uncertainty about effective use. Interaction may be sporadic, alternating between AI-supported and traditional approaches, or avoiding AI in certain task phases. This can be interpreted as a response to both cognitive factors—difficulties in interpreting AI-generated representations—and affective factors, such as concerns about reliability or academic appropriateness. While this tendency may reflect a form of critical stance that should not be dismissed, when it leads to avoidance rather than critical engagement, it may prevent students from developing the competencies required for effective AI use.

These three interaction tendencies—exploratory, efficiency-oriented, and cautious—are not mutually exclusive or stable traits. A single student may adopt different modes across phases of a task, depending on complexity, time constraints, and tool familiarity. What is particularly relevant from an educational perspective is that these tendencies correspond to different configurations of cognitive engagement. The three tendencies presented here are intended as illustrative rather than exhaustive; other configurations may exist, and mixed patterns—where elements of different tendencies coexist within the same student and task—are to be expected. Nevertheless, their recurrence suggests they capture meaningful differences in how students interact with AI during design activities, and in how AI mediates the relationship between intention, action, and evaluation.

5. Interaction Dimensions

The interaction tendencies described above can be further analyzed through a set of underlying dimensions that structure how students engage with AI systems during design activities. While tendencies capture recurring behavioral patterns, these dimensions provide an analytical lens allowing interaction to be decomposed into key components that vary independently and recombine in different configurations.

Three dimensions are particularly relevant in the context of AI-mediated product representation tasks. They are interdependent and jointly shape interaction dynamics and resulting learning processes.

The first dimension, goal formulation, concerns how students define and refine their design intentions when interacting with AI. In AI-supported contexts, goals must be articulated as prompts or structured inputs, making the process both more explicit and, in some cases, more constrained. Students differ significantly in how they approach this. Some treat prompts as flexible and evolving constructs, revising them iteratively in response to AI outputs—an ongoing process intertwined with exploration and reflection. Others adopt a more static approach, attempting to define a complete prompt from the outset, expecting a satisfactory result in a single step. Iterative goal formulation tends to support deeper engagement, while static formulation may lead to more procedural AI use.

The second dimension, interpretation of outputs, relates to how students make sense of AI-generated representations. Unlike manually produced representations, AI outputs often incorporate elements not explicitly specified, requiring interpretation beyond simple verification. Students must assess output relevance, identify implicit assumptions, and determine alignment with design intentions. Some engage in active interpretation—critically analyzing outputs, comparing alternatives, identifying strengths and limitations—which supports reflection and makes implicit aspects of design more explicit. Others adopt a more passive stance, accepting outputs at face value if they appear to meet task requirements. The ability to interpret AI-generated outputs is closely linked to the development of appropriate mental models; students who understand, even at a basic level, how AI generates outputs are better equipped to evaluate their reliability and use them effectively.

The third dimension, distribution of agency, concerns how control and initiative are shared between student and AI system. In traditional design, agency is largely centered on the human, with tools providing passive support. In AI-mediated contexts, the system can generate suggestions, propose alternatives, and influence the direction of the process. In exploratory interaction, agency is dynamically negotiated, with the student maintaining overall control while leveraging AI-generated alternatives. In efficiency-oriented interaction, a portion of agency is delegated to the system, relied upon to produce acceptable solutions with minimal user intervention. In cautious interaction, agency remains primarily with the student, but the potential contribution of AI is underutilized. The challenge lies in achieving a balance in which AI supports without replacing critical cognitive functions [11]. When too much control is delegated to the system, students may disengage from the reasoning process; when the system is underutilized, students may fail to benefit from its capabilities.

These three dimensions provide a coherent framework for analyzing interaction without requiring rigid classification of users or behaviors. From an educational perspective, they offer a basis for intervention: rather than categorizing students, educators can focus on how these dimensions are enacted and how they can be guided to support learning. Activities can be designed to encourage iterative goal formulation, to promote critical interpretation of outputs, and to foster a balanced distribution of agency—using the dimensional view as a bridge between descriptive observations and pedagogical strategies.

6. Discussion

The analysis presented in previous sections highlights that the educational impact of generative AI cannot be adequately understood through a tool-centered perspective. The quality of learning is shaped not by the capabilities of AI systems alone, but by how interaction with these systems unfolds during task execution. Interaction dynamics emerge as a central factor in determining whether AI supports or hinders meaningful engagement.

A first important implication concerns the role of interaction as a mediating layer between technology and cognition. Generative AI does not simply provide outputs; it actively participates in the representational process, influencing how students formulate problems, explore alternatives, and evaluate solutions. This aligns with perspectives in Human-AI interaction that emphasize user experience as shaped by the design of interaction rather than system performance alone [4] [5].

The identification of distinct interaction tendencies reveals that variability in user behavior is structurally relevant. Students engage with AI through qualitatively different modes that correspond to different levels of cognitive engagement. This challenges the implicit assumption that a single model of AI use can be equally effective for all students. In many educational contexts, AI tools are introduced without explicit guidance on how they should be used, risking the reinforcement of suboptimal forms of engagement—efficiency-oriented students may continue to use AI in a purely instrumental way, while cautious students may never develop the competencies needed to integrate AI effectively.

The analysis of interaction dimensions provides a conceptual bridge between observed behavior and potential interventions. By focusing on goal formulation, interpretation of outputs, and distribution of agency, it becomes possible to identify underlying mechanisms that shape interaction—levers through which engagement can be influenced through both system design and pedagogical strategies.

The notion of agency in AI-mediated contexts deserves particular attention. The presence of generative AI introduces a form of distributed agency, in which both human and system contribute to the development of representations. This challenges traditional views of design as a primarily human-driven activity and raises questions about authorship, responsibility, and control. The balance of agency appears to be a critical factor in interaction quality. The concept of human-centered AI emphasizes designing systems that augment rather than replace human capabilities [5], but achieving this goal requires not only appropriate system design but also explicit attention to how interaction is structured in educational contexts. Human-centeredness is not an inherent property of AI systems, but an emergent characteristic of the interaction between user, system, and task.

The temporal dimension of interaction also deserves consideration. The speed at which generative AI produces outputs can significantly alter the rhythm of the design process. While rapid generation enables efficient exploration, it may reduce time available for reflection, leading to more superficial engagement. Designing activities that intentionally introduce pauses—such as requiring explicit evaluation or comparison before proceeding—may help counterbalance this effect.

Finally, these considerations raise questions about assessment. Traditional evaluation methods focused on final outputs may not adequately capture the quality of interaction with AI systems. Since learning in AI-mediated contexts is closely linked to the processes through which outcomes are produced, assessment should take into account aspects such as iteration, critical evaluation, and decision-making rather than solely what students produce.

7. Teaching Implications

The analysis of interaction tendencies and underlying dimensions suggests that integrating generative AI into engineering education requires deliberate pedagogical design. Teaching practices must evolve to address not only what students produce, but how they interact with AI in the process of producing it. The three interaction dimensions identified in Section 5 suggest concrete teaching moves, summarized in **Table 2**.

A first implication concerns the design of learning activities. Tasks should be structured to encourage active engagement with representations rather than passive acceptance of system outputs. This can be achieved by shifting the focus from single-solution tasks to activities that explicitly require comparison, iteration, and justification. Rather than asking students to generate a single design proposal, instructors can require development of multiple alternatives with a critical analysis

Table 2. Interaction dimensions and associated teaching moves for AI-supported engineering design tasks.

Interaction Dimension	Concrete Teaching Move	Description
Goal formulation	Prompt revision	Students reformulate prompts across multiple iterations and reflect on how changes in formulation affect AI outputs
Output interpretation	Structured output critique	Students annotate AI-generated representations, identifying what works, what is missing, and what assumptions are embedded
Agency distribution	Design justification task	Students produce a written account explaining which AI outputs were selected or rejected and how their own reasoning shaped the final result

of their differences, making the interaction process visible and encouraging deeper engagement with the representational space. A concrete teaching move associated with this dimension is prompt revision: requiring students to reformulate their prompts across multiple iterations, and to reflect on how changes in formulation affect the outputs generated, makes goal formulation an explicit and observable part of the learning process.

A second implication relates to the role of iteration. Teaching strategies should aim to structure iterative processes meaningfully, for instance by setting explicit requirements for the number of iterations, defining criteria for comparison, or introducing checkpoints where students reflect on the evolution of their ideas. By doing so, iteration becomes a tool for learning rather than a byproduct of tool usage.

Interpretation of AI-generated outputs represents another key area for intervention. Students need to develop the ability to critically evaluate AI-produced representations, identifying strengths and limitations. Instructors can support this by incorporating activities that focus explicitly on interpretation—asking students to identify assumptions embedded in AI outputs, detect inconsistencies, or propose improvements. These practices help students develop a more reflective and informed approach to AI use. A concrete teaching move for this dimension is structured output critique: students are asked to annotate AI-generated representations, explicitly identifying what works, what is missing, and what assumptions are embedded in the output, before deciding how to proceed with their design.

The distribution of agency between students and systems also warrants pedagogical attention. As AI takes on a more active role in producing representations, there is a risk that students may relinquish control, adopting a passive stance. Teaching practices should emphasize the student as the primary agent in the design process—requiring justification of choices, explanation of how AI outputs have been modified or integrated, and demonstration of ownership of the final result. At the same time, an overly restrictive approach that limits AI's potential benefits should be avoided; the goal is to ensure AI supports rather than replaces cognitive engagement. A concrete teaching move for this dimension is the design justification task: students are required to produce a brief written account explaining which AI-generated outputs they selected or rejected, why, and how their own reasoning shaped the final result, making agency an explicit and assessable component of the learning process.

AI literacy should also be integrated into the curriculum as a transversal competence. This includes not only technical skills such as prompt formulation, but higher-level abilities related to interpretation, evaluation, and critical judgment. Practical steps may involve sessions dedicated to exploring AI behavior, discussing how outputs are generated, and highlighting common limitations such as bias or inconsistency. This perspective is consistent with approaches that emphasize complementarity between human instruction and AI-based support [12].

The role of the instructor is significantly transformed in AI-mediated environments. Rather than acting primarily as a source of knowledge, the instructor becomes a facilitator of interaction—monitoring how students engage with the system, identifying patterns, and intervening when necessary to promote more reflective forms of engagement. When students adopt an efficiency-oriented approach, the instructor can introduce constraints requiring deeper analysis; when students exhibit cautious interaction, additional support can build confidence and familiarity; when interaction is exploratory, the challenge may be to help students converge without prematurely limiting exploration.

Finally, assessment approaches need to evolve. Process-oriented assessment—where students document their interaction with AI, reflect on their decisions, and demonstrate how their ideas have evolved—provides a more accurate picture of learning than evaluation of final outputs alone, while reinforcing the importance of interaction as a central component of the educational experience.

8. Limitations

The present study adopts a conceptual and interpretative approach, which entails some limitations. First, the analysis is not based on newly collected empirical data but on the reinterpretation of existing knowledge and observations from educational practice. The interaction tendencies and dimensions discussed should therefore be understood as analytically grounded constructs rather than empirically validated categories. Second, the focus on product representation tasks in engineering education limits the scope of the findings; further research is needed to explore how interaction dynamics manifest in different disciplinary contexts. Third, the level of abstraction intentionally maintained to preserve flexibility means that translation into concrete educational practices requires further elaboration. Finally, the rapid evolution of generative AI technologies introduces uncertainty: as systems become more capable and interaction modalities evolve, the patterns described may also change, highlighting the need for ongoing research that continuously reassesses the relationship between AI capabilities, interaction processes, and learning outcomes.

9. Conclusions

The increasing integration of generative AI into engineering education is reshaping the nature of interaction between students, representations, and design processes. As this paper has argued, the educational impact of AI cannot be adequately understood by focusing solely on system capabilities or student perceptions; it is essential to consider how interaction unfolds during task execution and how it influences cognitive engagement.

By examining recurring interaction tendencies and articulating key dimensions—goal formulation, interpretation of outputs, and distribution of agency—this study has provided a conceptual lens for understanding variability in students' engagement with AI-supported design tasks. These dynamics reveal that the same technology can lead to substantially different learning experiences depending on how it is used, highlighting the central role of interaction in mediating the relationship between AI and learning.

From an educational perspective, effective integration of AI requires a shift toward interaction-centered pedagogies. Rather than treating AI as a neutral support tool, educators need to actively design and guide how students engage with these systems, promoting forms of interaction that support reflection, critical evaluation, and meaningful exploration. The value of AI in education lies not only in what it can generate, but also in how it can be used to enrich the learning process. The challenge is not to determine whether AI should be used in engineering education, but to understand how it can be integrated in ways that enhance the depth and quality of learning.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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