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Cognitive Implications of Using GenAI in Design Thinking: Insights From Educational Case Studies

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Abstract

Generative artificial intelligence (GenAI) is reshaping knowledge-intensive industries, requiring knowledge workers to adapt and, at times, reinvent their practices. Educating the next generation of knowledge workers in this rapidly evolving era of GenAI requires higher education to prepare students for this new work environment by incorporating GenAI-augmented practices into the educational process. This study investigates the integration of GenAI tools in design thinking (DT) workshops and examines their behavioral and cognitive implications across two educational settings. Drawing on data from two case studies and using a mixed-method research approach, we analyzed students' experience with and without the use of GenAI in both real and simulated customer contexts. Our findings reveal that GenAI integration transformed the practice of DT. Qualitative analysis of students' prompting practices revealed limited sophistication, with most students copying task guidelines directly and accepting AI-generated content without iteration, effectively exhibiting "metacognitive laziness." However, in authentic project contexts, students demonstrated more structured approaches. Quantitatively, students reported overwhelmingly positive perceptions of GenAI integration, with surveys showing notable improvements in perceived capabilities and self-efficacy compared with baseline conditions. Context-dependent differences emerged, with authentic project settings consistently associated with higher performance across all DT stages compared with hypothetical scenarios. This research contributes to the emerging discussion on the use of GenAI in design tasks by providing empirically grounded insights. It further proposes a GenAI-DT framework that facilitates authenticity and cognitive forcing processes to prevent cognitive degradation and promote critical thinking.

Keywords
cognitive forcing; critical thinking; design thinking; generative artificial intelligence; software engineering

1. Introduction

The introduction of generative artificial intelligence (GenAI) and its ever-evolving capabilities have dramatically changed the work practices of knowledge-intensive practitioners, requiring adaptations in skill sets and processes. In particular, in the software engineering domain, GenAI is used extensively throughout the entire software development life cycle (Nguyen-Duc et al., 2025). Acknowledging this paradigm shift, higher education institutions bear the responsibility of equipping future technology developers with the necessary proficiencies to meet the new demands and expectations of industry (Pervaiz et al., 2025). Since an important part of learning involves authentic experiences, such as engagement with real-life scenarios (Miranda et al., 2021), preparing students for GenAI-integrated work should involve hands-on team exercises that integrate GenAI as a partner within student teams while addressing real-world challenges (Zhou et al., 2024). On the other hand, studies have shown that while introducing GenAI tools into academia reduces cognitive load, such tools may also diminish intellectual capabilities (Gerlich, 2025; Irfan et al., 2023; Stadler et al., 2024; Zhang et al., 2024), thereby requiring cognitive forcing functions to elevate and restore them (Buçinca et al., 2021). Therefore, GenAI should be integrated cautiously, with careful consideration of these risks and mitigation strategies.

Teaching methods and learning activities in higher education have evolved from traditional training toward the development of new skill sets, such as ideation, technical prototyping skills, and the ability to reflect, remix, and synthesize GenAI- and human-generated ideas (Pervaiz et al., 2025; Sandhaus et al., 2025). Accordingly, higher education should foster: (a) critical thinking, which provides opportunities for students to immerse themselves in real-life problems by implementing different problem-solving techniques; (b) cooperation, through activities that promote group work, shared responsibility, and communication and collaboration during complex problem-solving; (c) presentation skills (e.g., pitches and project explanations), through activities that foster the ability to express ideas effectively in oral, graphical, and written forms, supported by technological infrastructures; and (d) creativity and innovation, through activities that encourage the development of novel problem solutions that provide new services, processes, systems, or practices for specific users (Gafni et al., 2023; Miranda et al., 2021). In this regard, design thinking (DT), a user-centered methodology, has become widely adopted, drawing on "design tools" to drive innovation, organizational competitiveness, and performance (Chen et al., 2025). However, the integration of GenAI into DT, its manifestations as well as its benefits and risks, has yet to be fully understood. In this article, we define GenAI-DT as the integration of GenAI tools into the practice of DT.

This research aims to shed light on how students practice GenAI-DT. The main research question guiding this study is: How is the use of GenAI-DT manifested in students' experiences? In particular, we asked the following sub-questions in each case study:

RQ1: How do students practice the different stages of DT using GenAI-DT?

RQ2: What are students' perceptions of the contributions of the GenAI-DT process?

To answer the RQs, we conducted two educational case studies that differed in student characteristics, timeframes, workshop medium, and challenge authenticity. In both cases, students practiced DT first without, and then with, the use of GenAI tools. The application of the DT methodology encompassed the Empathy, Define, Ideation (including Divergent and Convergent Ideation), and Prototype stages (Brown, 2008). In the first case study, the DT workshop was conducted in person during an advanced requirements engineering course for graduate students in information systems and was based on a topic chosen by the students and a respective hypothetical customer. In the second case study, the DT workshop was conducted virtually, using Zoom as the communication platform and a virtual collaborative environment, and involved final-year undergraduate information systems students participating in the capstone project course. In this case, students worked with real customers and had already elicited information about their requirements.

Using a mixed-methods research approach, our analysis revealed the benefits gained from these learning experiences, particularly when authentic data were used. The analysis also provided insights into the influence of GenAI-DT on cognitive involvement, distinguishing between effective cooperation with GenAI and excessive reliance on it, particularly during the ideation phases, in which increases in creative thinking metrics were observed. The research findings were further compared with a previous study in which students practiced DT without using GenAI (Levy & Hadar, 2024), serving as a baseline and providing additional validation of the perceived benefits across all GenAI-DT stages.

Our findings highlight the benefits and risks of using GenAI-DT, as well as the roles of authentic context and data in this experience. Based on these findings, we developed a GenAI-DT framework that facilitates authenticity and cognitive stimulation processes to prevent cognitive degradation and promote critical thinking. This framework may serve as a guide for designing effective and beneficent GenAI-DT implementations in educational settings, with some of this guidance potentially transferable to the general integration of GenAI in education and the practice of software engineering and beyond.

The remainder of the article is organized as follows. Section 2 reviews relevant theoretical background. Section 3 presents the research methodology, describing the two case studies. Section 4 reports the results, followed by a discussion in Section 5. Finally, Section 6 concludes the article.

2. Background

2.1. Human–AI Interaction

Effectively integrating AI into professional workflows requires addressing the uncertainty and probabilistic behaviors inherent in these systems. Amershi et al. (2019) developed design guidelines to manage such interactions across four phases: “Initially” (setting expectations), “During interaction” (providing context), “When wrong” (facilitating correction), and “Over time” (learning from behavior). These guidelines are essential because trust is a primary determinant of AI adoption. Gerlich (2024) identifies a “dichotomy of trust,” whereby many users perceive AI as more impartial and objective than humans, who are often viewed as having personal agendas. While this perception drives engagement, it remains fragile and susceptible to concerns regarding data privacy and system misuse.

This reliance on AI frequently leads to "cognitive offloading," a process in which individuals use external tools to reduce internal information-processing demands based on metacognitive evaluations of their own capacities (Risko & Gilbert, 2016). In the context of GenAI, this behavior shifts the cognitive burden from drafting and information gathering toward "information verification," "response integration," and "task stewardship" (H. P. Lee et al., 2025). However, this shift also introduces risks to critical thinking. H. P. Lee et al. (2025) found that while professional self-confidence encourages healthy scrutiny of AI, high confidence in AI capabilities often correlates with decreased critical thinking. This suggests that without sufficient professional confidence or task stakes, users may default to erroneous reliance on AI outputs.

2.2. GenAI and Education

GenAI has a profound influence on learning, creativity, problem-solving, and other cognitive operations and skills. Kosmyna et al. (2025) demonstrated both transformative benefits and potential drawbacks through neural engagement studies of integrating GenAI into human cognitive and educational processes. GenAI significantly enhances learning by personalizing educational experiences, providing immediate feedback, and reducing cognitive load through the automation of routine tasks such as summarization, drafting, and coding assistance. These capabilities free learners to focus on higher-level thinking, creativity, and problem-solving. GenAI can further accelerate ideation, automatization, and design optimization, and support seamless idea generation, fast and cheap prototyping and iteration, and time efficiency (Popescu & Schut, 2023).

However, overreliance on GenAI can lead to shallow learning, diminished critical thinking, and reduced engagement in reflective or effortful cognitive practices. Students may experience a loss of originality and creative writing ability, become prone to metacognitive laziness, defined as "learners' dependence on AI assistance, offloading metacognitive load, and less effectively associating responsible metacognitive processes with learning tasks" (Fan et al., 2025), and suffer long-term skill atrophy (Zhou et al., 2024). GenAI may promote convergent thinking, whereby users overly depend on AI-generated suggestions, potentially undermining independent reasoning. This overdependence contributes to "cognitive debt," a trade-off in which the short-term ease and efficiency provided by AI erode in-depth learning and creativity. Recent empirical studies indicate that AI-assisted writing produces weaker neural engagement compared with brain-only writing (Kosmyna et al., 2025).

In addition, cognitive biases such as prompt bias, whereby designers subconsciously favor certain prompts, can limit creative exploration, as poor input produces skewed outputs that reinforce user preconceptions (Popescu & Schut, 2023). Even after explainable AI was introduced to address overreliance by providing explanations for AI recommendations, studies have shown that such explanations often do not significantly reduce overreliance and, in some cases, may even increase it. This is because people tend to interpret explanations as a general signal of competence rather than analytically evaluating them, since engaging with explanations requires substantial cognitive effort (Zhang et al., 2024).

2.3. GenAI and DT

The integration of GenAI into DT processes in academic contexts is a rapidly growing area of research, highlighting its potential to enhance creativity, problem-solving, and innovation (Havidotinnisa et al., 2024; Weng et al., 2024). GenAI is recognized as a disruptive technology that enhances efficiency and supports sustainable business models, human-centered solutions, and adaptive innovation in DT (Havidotinnisa et al., 2024). Its tools facilitate creative human–technology collaboration, enabling designers to ideate and iterate more efficiently by providing novel interactions, generating new ideas for various tasks (Sandhaus et al., 2025), and broadening the range of responses students might not otherwise achieve, thereby supporting knowledge creation (A. V. Y. Lee et al., 2024).

However, the integration of GenAI into DT processes also presents cognitive barriers that may hinder creativity and effective problem-solving. Research indicates that, while enhancing design efficiency, GenAI introduces cognitive biases and challenges that designers must navigate, such as the aforementioned prompt bias. GenAI tools may also amplify/deepen pre-existing cognitive biases, affecting the ideation phase and potentially stifling innovation (Popescu & Schut, 2023). Importantly, GenAI's rigid programming restricts its ability to replicate human creativity, which is essential in design and other creative fields (Havidotinnisa et al., 2024).

2.4. GenAI and Cognitive Forcing

Cognitive forcing includes interventions applied at the moment of decision making to disrupt heuristic reasoning that leads to cognitive biases (Kahneman, 2011) and, instead, compel individuals to engage in more analytical and effortful thinking (Buçinca et al., 2021). In AI-assisted decision making, cognitive forcing aims to overcome users' overreliance on AI-powered decision support tools, which can sometimes result in poorer performance with the AI alone (Buçinca et al., 2021). Examples of cognitive forcing interventions include: asking users to make a decision before seeing the AI's recommendation, reducing the anchoring bias whereby initial decisions are influenced by AI suggestions if presented first (Buçinca et al., 2021); slowing down the process by delaying presentation of the AI's recommendation to motivate users to form their own hypotheses in the interim, and only then evaluate the AI's explanation against their own (Park et al., 2019).

Studies have shown that cognitive forcing functions significantly reduce overreliance on AI, leading users to make more correct decisions when the AI's predictions are incorrect, compared with users of simple explainable AI approaches. Buçinca et al. (2021) also indicate perceived usability and acceptability concerns when adding cognitive forcing functions and recommend exploring adaptive strategies and devising cognitive forcing interventions that actively elicit analytical thinking when necessary to prevent unquestioning trust. Further research is needed to determine the optimal amount and timing of cognitive forcing for different users.

3. Method

3.1. Research Approach

The research consisted of two case studies conducted in educational contexts, differing substantially in their settings and populations (as described below). We used a mixed-methods approach to collect and analyze the data, aiming to combine an in-depth understanding of students' practices and perceptions, supported by the qualitative approach, with comparisons between different settings, enabled by quantitative tools. Data collection was performed after the students had completed the DT workshop and included the submitted artifacts and a reflection survey. The reflection survey was based on a questionnaire from a previous study

(Levy & Hadar, 2024) and aimed to capture students' perceptions of their DT experience, enabling measurement of the percentage of participants agreeing with the expected benefits from each DT phase; for example, the percentage of students who agreed with the benefit "allowed me to understand and define the challenge better," from the Empathy phase of DT (Brown, 2008).

Participation in the survey was voluntary and anonymous, following ethical principles and approved by the IRB. The questionnaire included open-ended questions for qualitative data collection and closed-ended questions to quantify participants' opinions about their experience during the workshop. We used the exact version used in Levy and Hadar (2024) despite its limitations (the questions were constrained by the original study to binary agree/disagree rather than Likert scale-based responses) to allow comparison of the current results with those of the previous study. The questionnaire is available at https://drive.google.com/file/d/135l-nmLDyDJr43Ntzx_XReGcifY6bPYr/view.

3.2. Settings and Procedure

Case Study 1 took place in an academic college, during an advanced requirements engineering course for MSc students in information systems. All 24 enrolled students participated in the course's in-person DT workshop, which comprised two 2.5-hour sessions. The students held BSc degrees and had previous work experience in information systems. Six teams, of four students each, worked on hypothetical projects of their choosing, conceived specifically for the workshop.

The workshop began with an introduction to DT, after which the lecturer presented each step and its execution instructions. Teams then performed each step twice: first without and then with the use of GenAI. The students downloaded the PowerPoint presentation containing the instructions and worked on the tasks directly in the presentation. The slides provided guidelines for the five DT steps, Empathy, Define, Ideate (Divergent), Ideate (Convergent), and Prototype, using relevant tools such as Persona and Empathy Map. The students practiced first on data collected for their hypothetical projects, then uploaded the data to GenAI, and prompted it with DT guidelines to expand their original outcomes. They could use any GenAI tool they were familiar with or had a legal license for. Finally, all students were required to submit their artifacts, and were invited to complete a voluntary reflection questionnaire; 12 of the 24 participants responded.

Case Study 2 took place at a university during a capstone project course for final-year undergraduate students in information systems. The DT workshop was offered as part of the course's enrichment lecture. By that stage, students had completed most BSc requirements, including courses on software analysis and design, introductory and advanced programming and databases. A total of 102 students participated in the DT workshop, conducted in a single 1.5-hour session. Participants worked in teams of two to three students, the same teams assigned to their year-long capstone projects developing information systems for real clients. Prior to the session, teams were asked to prepare and bring materials collected from their clients to support requirements analysis. The DT workshop took place mid-semester, after several weeks during which students collected the requirements. The workshop was conducted virtually via Zoom, and teams were instructed either to meet physically in a shared location or to collaborate online using a preferred application.

Here too, the workshop began with an introduction to DT, after which the lecturer presented each step and its execution instructions. Teams were given limited time for each step, to ensure the entire procedure was completed within the 90-minute timeframe. Teams completed all the steps first without using GenAI and then repeated the entire process using GenAI. The students downloaded the PowerPoint presentation containing the instructions and worked on the tasks in the PowerPoint file. Finally, all students submitted their artifacts and were invited to complete a voluntary reflection questionnaire; 75 of the 102 participants responded.

3.3. Data Analysis

The qualitative data gathered from the questionnaire's open-ended questions underwent thematic analysis (Cruzes & Dybå, 2011) using an interpretive research framework (Walsham, 2006). This approach aligns with our objective of understanding the subjective meanings students assign to their practices and perceptions. Data analysis was further applied to the prompts documented/reported in students' submitted artifacts as a complementary data source to the questionnaire findings.

Data were analyzed using an inductive thematic approach, in which categories emerged directly from the data and were iteratively refined (Cruzes & Dybå, 2011; Strauss & Corbin, 1990). The analysis followed the systematic procedure of open, axial, and selective coding to identify recurring themes and define their dimensions (Strauss & Corbin, 1990). Trustworthiness (Cruzes & Dybå, 2011) was ensured as the first and third authors coded the data independently and then reviewed the resulting codes with the other authors, identifying and resolving disagreements. Prompts and reflections were rechecked and recoded as needed to ensure accurate and coherent classification and interpretation.

For example, a student's statement that GenAI "focused on relevant ideas in the fastest and easiest way" was first grouped to form a theme called Focused Guidance and Asking Questions, which was ultimately placed under the higher-order category of GenAI Contribution to Thinking Skills. This revealed that students viewed GenAI as a guiding partner that helps them stay focused and systematic throughout the project, going beyond simple content generation to provide a cognitive benefit. Another example is the quote, "I took the prompts straight from the slides," which was initially coded as Prompt Copying, defined as transferring instructions directly into a prompt for GenAI without adaptation. This code was later grouped with other similar behaviors to form the broader theme of Metacognitive Laziness, which describes students' limited critical thinking engagement when using GenAI.

As a complementary (quantitative) analysis, we calculated the percentage of participants' agreement with the expected benefits from each DT phase, comparing the agreement percentage per statement between the case studies. We compared the average agreement level (percentage of students who agreed with the statements) in both case studies after using GenAI with the average agreement level reported in previous research in which GenAI was not used as baseline data (Levy & Hadar, 2024). We did this instead of comparing students' reflections on the two conditions they experienced (with and without GenAI) during this study because the reflection questionnaire was completed after the session, when the students had already used GenAI.

4. Findings

4.1. GenAI-DT Practice

To answer RQ1, namely, how students practiced the different stages of DT using GenAI, we analyzed their prompting practices and their acceptance of AI-generated content.

Our main observation is that the variety and richness of the prompts used were very limited; the most salient practice was copying the exercise guidelines as they were, with no (or almost no) additions or changes, and often using the generated content as is, without editing it or further iterating through additional prompts for refinement. Several students explicitly stated they "took the prompts straight from the slides" or "I literally pasted this." More specifically, in the Empathy stage, students leveraged GenAI to rapidly create detailed personas and empathy maps, with prompts such as "Create a persona of a forklift technician" and "Help me create a persona and scenario for a parent concerned about their child's anxiety." During ideation, GenAI facilitated both divergent thinking through requests such as "Generate 10 wild solution ideas—quantity over quality" and convergent thinking for refinement: "From the 10 ideas above, pick one best-bet concept and list 4–6 high-level requirements." In the prototype stage, students found that "one prompt produced a full MVP architecture" and appreciated how "it helped me convert functional requirements into design ideas quickly."

This finding aligns with the "metacognitive laziness" phenomenon defined by Fan et al. (2025). Interestingly, despite the widespread demonstration of this behavior in both case studies, we identified that participants in Case Study 1 used more general prompts, such as "Give me more ideas" for content generation, while those in Case Study 2 demonstrated somewhat more sophisticated, structured approaches with specific prompts such as "Build an empathy map (in the next slide) according to your insights from the previous step." This suggests varying levels of sophistication in how students integrate GenAI into their DT practice. This may stem from the authentic context of the task of Case Study 2, which was based on real customers and projects.

4.2. Perceptions About GenAI in the Context of DT

To answer RQ2, namely, students' perceptions of the contributions of the GenAI-DT process, we qualitatively analyzed responses to the open-ended questions in the reflection questionnaire. The thematic analysis identified key patterns in how students described GenAI's role, including its ability to expand creative boundaries, provide focused guidance, and assist in organizing and evaluating ideas. These qualitative insights, detailed in Table 1, help explain the mechanisms behind the quantitative improvements observed and provide context for understanding what participants valued most about AI integration in DT activities.

Table 1 summarizes three main themes: (a) GenAI's Contribution to Thinking Skills (T1, T2, T3), (b) AI as an Empathy Facilitator (E1, E2), and (c) AI as a Designer (D1, D2, D3). For each theme, the table presents the relevant categories, their descriptions, and illustrative citations. For example, the category Critical Thinking and Feedback is described as "AI's role in providing constructive criticism and evaluation from multiple perspectives." In Case Study 1, a student referred to this category negatively, stating: "It didn't really tell me anything I didn't know." In contrast, in Case Study 2, a student described a positive experience: "It allowed me to refine my thinking more effectively."

Table 1. Main themes and categories from reflection analysis, with example quotes from the case studies (negative feedback is indicated by the word "Negative").

Category	Description	Case Study 1 (Hypothetical)	Case Study 2 (Authentic)
		1. GenAI's Contribution to Thinking Skills	
T1. Expanding the boundaries of thinking and creativity	AI's ability to push participants beyond conventional thinking patterns and generate novel creative solutions and various perspectives	"Expanded the boundaries of our creativity." "It opened our line of thought."	"The use of GenAI allowed me to focus more on critical thinking and content refinement rather than getting stuck on wording or format."
T2. Focused guidance and asking questions	AI's role in helping participants formulate better inquiries and identify knowledge gaps	"Focus on relevant ideas in the fastest and easiest way."	"It made it very easy to organize our thoughts and progress through the various stages of the task."
T3. Evaluating and prioritizing ideas	AI's assistance in organizing, clarifying, and prioritizing ideas		"The GenAI tool helped me organize my thoughts, evaluate ideas more critically, and communicate our final solution clearly and confidently. It made the decision-making process faster and more structured."
T4. Time saving and efficiency	AI's impact on accelerating work processes while maintaining quality standards	"Delivered high-quality products in a short time; I would not have been able to achieve such high-quality products in a short time frame by myself."	"It allowed me to quickly generate diverse ideas, explore new directions I hadn't considered before."
T5. Critical thinking and feedback	AI's role in providing constructive criticism and evaluation from multiple perspectives	Negative: "It didn't really tell me anything I didn't know."	"Using the GenAI tool helped me approach this stage with more confidence and creativity." "It allowed me to refine my thinking more effectively."
		2. AI as Empathy Facilitator	
E1. Enhanced empathy and deeper understanding	Strengthening capabilities to comprehend user emotions	"It helped us map out all the relevant things for the persona from the simulated interviews we offered."	"Helped me understand the value of deep empathy for the user before jumping into solving their needs."
E2. Strengthening understanding of user needs	Enhanced comprehension of user challenges and functional requirements		"We received suggestions for personas, with a variety of precise wordings, emotions, and insights into the depth of user behavior."

Table 1. (Cont.) Main themes and categories from reflection analysis, with example quotes from the case studies (negative feedback is indicated by the word "Negative").

Category	Description	Case Study 1 (Hypothetical)	Case Study 2 (Authentic)
		3. AI as a Designer	
D1. AI as accelerator not replacement	Recognition that AI enhances rather than replaces human cognitive processes and creativity	"Doesn't replace human thinking—but accelerates creativity."	"Throughout the entire process, it felt like a silent partner constantly throwing in good ideas, structure, and clarity. It didn't replace my thinking but upgraded it."
D2. Formulating scenarios	AI's specialized capability in generating diverse user journey flows		"Helped understand the correct interface flow."
D3. Interface and prototype design	AI's contribution to visualizing, structuring, and presenting design concepts effectively	Negative: "Did not help much, we should have used other tools to design the screens."	"Using the tool helped me think of new ideas for how to visually present the interface and think about types of screens." "Made prototyping faster to design and more user-centric. I could think about the entire user journey, not just the functionality."

In Case Study 1, where students worked on hypothetical projects, they experienced GenAI as a supportive companion during the DT process. GenAI allowed human interaction and collaboration to drive the process while providing complementary support. Students used GenAI to enhance their existing team dynamics within the controlled exercise structure.

In Case Study 2, where students worked on authentic projects, they engaged with GenAI more directly. When defining problems, students relied on GenAI to guide them toward structured problem definition and analytical thinking. The use of GenAI-DT provided necessary scaffolding to help students navigate project ambiguity and uncertainty.

Across all DT stages, students (from both groups) utilized GenAI differently, as evident from Table 1. In the Empathy stage, GenAI helped students better understand and define challenges, particularly in grasping customer functional needs. The Ideation-Divergent stage showed enhanced GenAI support for leadership skills, intuitive thinking, and creative capabilities. In the Ideation-Convergent phase, GenAI assisted with analytical thinking and building upon existing ideas. Finally, in the Prototype stage, GenAI facilitated the realization of solutions and improved design and creative skills.

4.3. Students' Perceptions of DT Following Experience With vs. Without GenAI

As a complementary analysis (as depicted in Table 2), we compared the average agreement level (percentage of students who agreed with the statements) in both case studies after using GenAI with the average agreement level reported in previous research in which GenAI was not used as baseline data (Levy & Hadar, 2024). We did this instead of comparing students' reflections on the two conditions they experienced (with and without GenAI) during this study because the reflection questionnaire was completed after the session, when the students had already used GenAI.

In both cases, the Define stage, being a short phase, summarizing the Empathy stage, was included in the Empathy phase.

Table 2. Students' percentage of agreement with the DT task: Baseline, Case 1, Case 2.

Statement	Agreement percentage (no. of participants)		
	Baseline (25)	Case Study 1 (12)	Case Study 2 (75)
Empathy			
Allowed me to understand and define the challenge better	56% (14)	75% (9)	99% (74)
Allowed me to understand the customer's functional needs better	68% (17)	92% (11)	95% (71)
Allowed me to understand the customer's emotional needs better	56% (14)	100% (12)	88% (66)
Allowed me to understand the contribution of my system to the customer better	60% (15)	83% (10)	96% (72)
Ideation-Divergent			
Allowed me to understand my teammates' solutions better	48% (12)	92% (11)	96% (72)
Improved my listening skills	48% (12)	83% (10)	81% (61)
Improved my intuitive thinking skills	64% (16)	75% (9)	88% (66)
Improved my initial solutions	52% (13)	92% (11)	93% (XX)
Improved my creative skills	56% (14)	83% (10)	85% (64)

Table 2. (Cont.) Students' percentage of agreement with the DT task: Baseline, Case 1, Case 2.

Statement	Agreement percentage (no. of participants) Baseline (25)	Case Study 1 (12)	Case Study 2 (75)
Ideation-Convergent			
Allowed my team to arrive at agreed solutions	60% (17)	100% (12)	93% (70)
Improved my argumentation skills	36% (9)	92% (11)	85% (64)
Improved my analytic thinking skills	48% (12)	75% (9)	91% (68)
Prototype			
Allowed my team to better realize the agreed solution	68% (17)	92% (11)	83% (62)
Improved my design skills	48% (12)	75% (9)	76% (57)
Improved my creative skills	44% (11)	83% (10)	80% (60)

Looking at Table 2, students reported overwhelmingly positive perceptions of GenAI integration across all DT stages, with notable improvements in their perceived capabilities and self-efficacy when compared with the baseline condition without GenAI support.

Stage-specific perceptions revealed consistent improvements across all DT phases when AI was integrated. In the Empathy stage, both case studies significantly outperformed the baseline condition, with challenge definition improving from baseline to Case Study 1 and Case Study 2. The Ideation phases showed the most dramatic improvements, with some creative thinking metrics demonstrating nearly 40% increases over baseline conditions. Convergent ideation revealed enhanced analytical thinking progressing from baseline to Case Study 1 (75%) and Case Study 2 (100%). Finally, the Prototype stage showed clear advancement in team solution realization from baseline through Case Study 1 (75%) to Case Study 2 (92%).

Context-dependent differences emerged between the case studies as clearly demonstrated in Table 2, with both GenAI-integrated conditions outperforming the baseline data (Levy & Hadar, 2024):

- Baseline (no GenAI use): Represents the lowest performance levels across all metrics, establishing the starting point for measuring AI integration benefits.
- Case Study 1 (hypothetical, with GenAI): Achieved perfect scores in specific areas such as understanding customer emotional needs (100%) and consistent improvements over baseline across empathy metrics, with most scores ranging between 75% and 100%. While this seems impressive, we

must take into consideration the absence of a real customer, which limited opportunities to validate/confront the customers' understanding against/with real-life situations.

- Case Study 2 (authentic, with GenAI): Consistently achieved the highest performance across most metrics, particularly in challenge definition (99%), analytic thinking skills (100%), and team solution realization (96%). One possible explanation for this observation is that the combination of GenAI with an authentic context resulted in the highest perceived benefits.

5. Discussion

5.1. Implications and Utilization of the Findings

The quantitative results presented in Table 2 demonstrate consistently higher perceived benefits across all DT stages in the two case studies in which GenAI was used, compared with the baseline process performed without GenAI (Levy & Hadar, 2024). Our qualitative analysis reveals a certain contradiction between students' positive perceptions and their actual cognitive engagement, consistent with Kosmyna et al. (2025). While both case studies produced overwhelmingly positive perceptions regarding GenAI integration, the depth of the students' actual cognitive processing varied between the two studies, as evident in Table 1. Case Study 1 (Hypothetical) students emphasized generic efficiency benefits ("expanded the boundaries of our creativity," "focus on relevant ideas in the fastest way"), with some stating that AI "didn't really tell me anything I didn't know." Case Study 2 (Authentic) students, on the other hand, demonstrated deeper engagement, articulating specific cognitive operations ("organize my thoughts, evaluate ideas more critically"), demonstrating understanding DT principles ("deep empathy for the user before jumping into solving their needs"), and characterizing GenAI as a "silent partner" that "upgraded" rather than replaced their thinking. Furthermore, the quantitative difference observed between the two case studies (Table 2) may be explained by the use of GenAI within an authentic context (Case Study 2). This potential explanation, however, is based on highly imbalanced group sizes, with the group in Case Study 1 being relatively/quite small (12 participants), and is not supported by experimental settings. A large-scale experiment comparing these two conditions should be conducted to test this explanation.

Looking at our findings through the cognitive forcing lens (Buçinca et al., 2021), we may be able to address these challenges and harness the demonstrated benefits of the authentic GenAI-DT experience observed in Case Study 2. To demonstrate this approach, we propose an initial framework embedding cognitive forcing into GenAI-DT to mitigate metacognitive laziness when using AI. Several of the cognitive forcing activities presented below were inspired by literature on DT practices (Jiang & Pang, 2023; Levy & Hadar, 2024). The proposed AI Companion Agent would address metacognitive laziness by serving as a repository for team knowledge while simultaneously challenging users to maintain ownership of their cognitive processes. By integrating established cognitive forcing interventions, this approach can help overcome documented cognitive barriers in human–AI collaboration (Chen et al., 2025; Popescu & Schut, 2023). This may further help prevent the cognitive degradation that occurs when AI functions as a substitute rather than an enhancement to human thinking. This framework synthesizes our research findings into actionable design principles for the AI Companion Agent, adapted to each DT phase, with specific cognitive forcing actions tailored to promote authentic engagement and critical thinking. To strengthen the empirical grounding of this framework, we explicitly mapped the categories identified in our qualitative analysis (Table 1) to the proposed AI interventions in each DT phase. This mapping demonstrates how specific student behaviors and perceptions directly informed the design of cognitive forcing actions. The resulting solution could guide students, and possibly practitioners, through a more substantial DT process by ensuring continuous connection to real-world contexts and stakeholder needs, ultimately producing more realistic and meaningful outcomes than either traditional DT or current GenAI-DT implementations. Table 3 outlines key principles for cognitive forcing actions to be performed by the AI Companion agent in each DT phase,

Table 3. GenAI-DT phases guided by AI cognitive forcing actions, mapped to Table 1 categories.

Authentic context	Critical thinking	Proposed AI cognitive forcing actions	Observed behavior and GenAI-DT intervention
Empathy (Categories E1, E2)			
Inquiry facilitator Uploading a priori information of the context, stakeholders, customers, etc.	Breadth and depth validator Ensuring each element of the empathy map is grounded in reality, and exploring deeper insights about users.	Ask questions about the persona, interact with other stakeholders and technology (including sociocultural and socioeconomic aspects, technology adoption barriers, etc.). Ask questions about the existing user journey.	Behavior: Designer states user needs without supporting data or misses key stakeholder groups. Intervention: "This persona lacks socioeconomic context. What is this student's financial situation? Do they work while studying? What technology do they already use daily? How does their cultural background influence their conduct?"
Define (Categories E1, T3)			
Value mapper Ensuring the problem definition is well-grounded in the data and data sources.	Value crystallizer Crystalizing user needs, distilling and prioritizing the intended values and their recipients.	Ask questions about the value for the user. Identify user priorities. Map values to different users	Behavior: Designer states a solution rather than a problem, or problem lacks grounding in research or prioritizing. Intervention: "You've identified multiple values: convenience, cost savings, social connection, privacy. Let's map these: Which stakeholder values which outcome most? If users had to choose between privacy and social connection, what would they prioritize, according to your data?"
Ideation-Divergent (Categories T1, T2, T4)			
Creative brainstorming partner Encouraging the creation of features related to the values from the previous stage.	Not relevant for this stage.	Gradual idea generation: A "ping-pong" of mutual suggestions between AI and designer. Act as an active brainstorming partner by expanding on ideas proposed by either designer or AI. *Guideline: Every idea is met with a positive response and without criticism.*	Behavior: Designer proposes single idea or evaluates idea quality before generating alternatives. Intervention: "That's an interesting start—a notification system. Let's build on this: What if we also [suggest variation]? Thinking completely differently, what if instead of notifications, we explored a predictive dashboard? Your turn—take any of these in a new direction."

Table 3. (Cont.) GenAI-DT phases guided by AI cognitive forcing actions, mapped to Table 1 categories.

Authentic context	Critical thinking	Proposed AI cognitive forcing actions	Observed behavior and GenAI-DT intervention
	Ideation-Convergent (Categories T3, T5)		
Reality checker Providing constructive critique of generated ideas against user actual needs and helping map them along innovation dimensions.	Critical analyst Guiding the designer to critique ideas based on: user desirability, business/economic viability, and technological feasibility. Considering innovation vs. implementation feasibility.	Critique ideas. Map ideas on an axis of innovation vs. complexity Propose tools for analysis and requirements definition that address the desirability–technological feasibility–business viability triangle.	Behavior: Designer has multiple ideas but no evaluation framework or mapping. Intervention: "Let's map these ideas on two axes: innovation potential (low/medium/high) and implementation complexity (low/medium/high). Should we also create a desirability–feasibility–viability matrix?"
	Prototype (Categories D2, D3)		
Technical facilitator Ensuring the prototype is connected to reality and requirements.	Feasibility analyzer Eliminating unreasonable alternatives, simulating potential stakeholder responses to design decisions.	Suggest tools for building a prototype. Build the interface. Assist in analyzing alternatives for the prototype. Simulate stakeholder responses.	Behavior: Designer creates prototype without considering stakeholder reactions or constraints. Intervention: "I'm simulating a busy parent encountering your 5-step onboarding—likely drop-off at step 3 (photo ID upload). Simulating your IT stakeholder: GDPR compliance concerns for storing ID images. Should we explore alternative verification methods?"
	Test (Categories T5, D1)		
Interactive validator Presenting the prototype to different stakeholders.	Evaluation and refinement facilitator Analyzing the pros and cons of the solution, enabling more sophisticated testing cycles through automated analysis and iterative refinement suggestions.	Promote interactive conversation with the stakeholder and modify the prototype accordingly (e.g., based on sentiment analysis).	Behavior: Stakeholder provides vague feedback ("It's fine"). Intervention: "Let's dig deeper. I'll facilitate: 'Can you walk me through using this for your actual workflow? Where would you access this during your day? What would make you choose this over your current solution?'"

showing the explicit links between our empirical findings (mapped categories from Table 1) and the proposed interventions. These actions are designed to facilitate meaningful and in-depth dialogue with users in the DT process, ultimately leading to more substantial processes and more realistic outcomes. For example, the Empathy stage references categories E1 and E2, showing how students' reported experiences in understanding user emotions directly shaped the AI agent's "Inquiry facilitator" role. Similarly, the Ideation stages link to categories T1 and T2, demonstrating how students' perceptions of enhanced creativity informed the brainstorming partner design.

Finally, we embed the AI Companion Agent across all DT stages (Brown, 2008), where the GenAI-DT agent serves in different roles in each DT phase (see Figure 1).

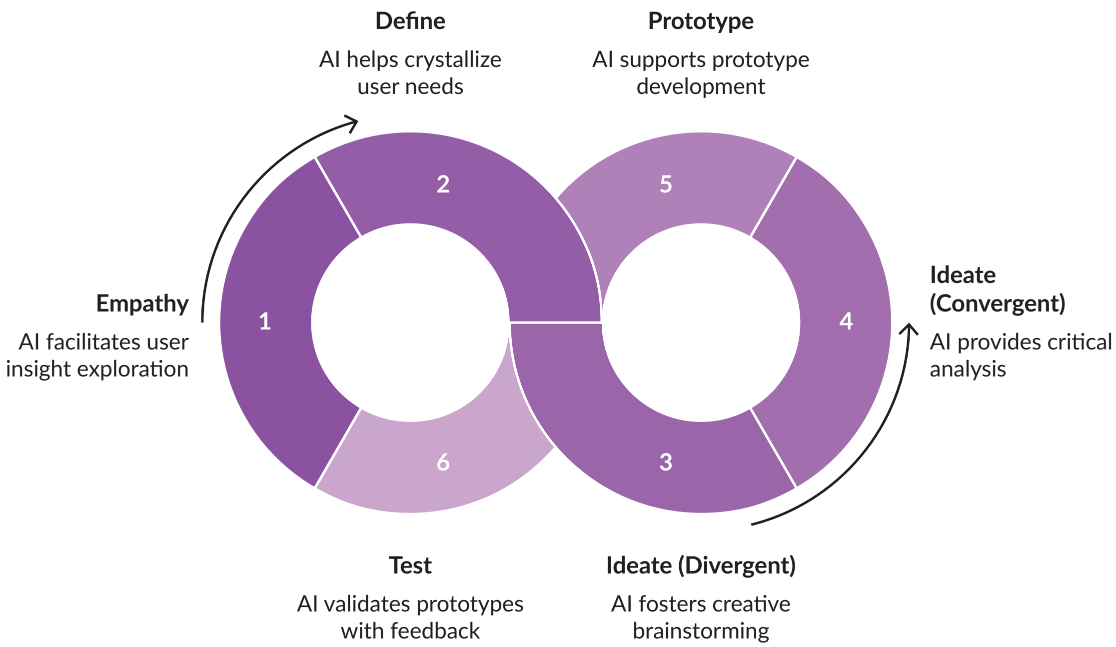

Figure 1. Enhanced GenAI-DT process.

Such a framework can be based on an AI Companion Agent model designed to function according to cognitive forcing principles rather than as a task-completion tool. This agent would serve as an intelligent guide that actively promotes human agency by consistently redirecting users back to real-world engagement with stakeholders and authentic problem contexts. Rather than providing ready-made solutions, the agent would employ deliberate cognitive forcing techniques, including response delays (Park et al., 2019), Socratic questioning methods, and structured prompts that require users to justify their thinking processes (Wei et al., 2023).

Following Buçinca et al.'s (2021) principle of cognitive forcing before decision making, our AI Companion Agent deals with each phase differently, and will address each phase with adequate prompts that lead it to function as a stimulator and guide for the human agent, supporting the co-creation of authentic personas and, accordingly, relevant solution ideas that align with the authentic context and challenge. This approach emphasizes that GenAI would act not merely as a tool for automation but as an active participant, enhancing human capabilities and fostering a more efficient, creative, and user-centered DT process.

5.2. Theoretical and Practical Contribution

This study provides insights revealing a dissonance that aligns with emerging research on GenAI's cognitive impact. Returning to Zhou et al.'s (2024) concern about skill atrophy, while students report satisfaction with

GenAI assistance primarily due to efficiency gains and reduced cognitive load, this convenience appears to undermine the learning objectives that the DT process aims to achieve. The positive perceptions mask a troubling trend toward cognitive outsourcing rather than cognitive enhancement, creating what researchers term "cognitive debt," i.e., short-term efficiency gains that erode long-term learning and thinking capabilities (Kosmyna et al., 2025). In our context, participants become satisfied with surface-level task completion while missing opportunities for deep empathetic reasoning, critical problem analysis, and creative problem-solving expected in a mindful DT process. This phenomenon mirrors previous findings in other AI-assisted domains, suggesting less diverse cognitive processing (Kosmyna et al., 2025).

The framework we propose incorporates cognitive forcing techniques to enhance users' critical thinking and problem-solving skills. The AI Companion Agent would delay responses and use the Socratic method to ask guiding questions, prompting designers to re-engage with the real-world context at every step. This approach is informed by research on techniques like chain-of-thought prompting (A. V. Y. Lee et al., 2024; Wei et al., 2023), which has been shown to improve interpretability and encourage learners to ask better questions. The agent's actions, as outlined in our framework, are intended to promote meaningful dialogue with designers, leading to more substantial processes and more realistic outcomes. For each DT phase, our model proposes specific cognitive forcing actions to be performed by the AI Companion Agent. These actions are designed to emphasize the need for authentic context and critical thinking, pushing designers beyond automated tasks and toward deeper engagement with the problem. This ensures that the process is not just fast but also meaningful and grounded in reality.

The study provides implications for integrating GenAI into DT. The findings highlight the urgent need for structured GenAI integration guidelines that preserve authentic learning while leveraging GenAI's collaborative potential. The challenge lies not in the technology itself, but in developing pedagogical frameworks and practical tools that encourage user engagement while preventing dependency. This requires explicit instruction on productive AI collaboration, metacognitive awareness training, and assessment methods that can distinguish between AI-enhanced thinking and AI-substituted thinking. Doing so would address the problem of the observed overdependence on AI, which results in convergent thinking patterns, where users become overly reliant on AI-generated suggestions, potentially undermining independent reasoning and creative problem-solving abilities (Chen et al., 2025).

5.3. Limitations

Several limitations of the study should be considered. For the main, qualitative part of the study, we examine the four elements of trustworthiness, namely, credibility, transferability, dependability, and confirmability (Guba, 1981), and discuss the respective limitations stemming from the study settings and methods.

Credibility (analogous to internal validity) is framed in positive terms and addresses the "truth" of the research findings. In this study, credibility is inherently threatened by the use of self-report as a data source for participants' perceptions and behaviors, which may be affected by self-serving or social desirability biases (van de Mortel, 2008). We attempted to mitigate these threats by assuring the participants that their data were fully anonymized. Nevertheless, these biases may have contributed/led to a somewhat optimistic picture. Acquiescence bias (Kenny & Acitelli, 2001), which can lead to falsely positive conclusions, may have further contributed to results that appear more optimistic than the actual situation. To improve credibility through an additional data source, we collected artifacts from GenAI-DT processes and analyzed them as complementary data to ensure, for example, that the activities the students reported on in the reflection questionnaire were also evident in their artifacts.

Transferability (analogous to external validity) addresses whether findings apply to other contexts or populations, and is inherently challenged in case-study research. To mitigate this limitation, we conducted two case studies that differed substantially in population, settings, duration, and project type (real vs. hypothetical). This approach enables comparison across different conditions and extends the contexts in which our approach and outcomes may be applicable.

Dependability (analogous to reliability) addresses the consistency and replicability of findings. Following coding agreement among authors, data were re-analyzed to ensure consistency using stepwise replication and dependability audits (Guba, 1981).

Confirmability (analogous to objectivity) addresses the neutrality of findings. To reduce bias, we employed (a) triangulation across multiple data sources and settings, and (b) mixed researcher involvement, whereby one author interacted directly with participants while others remained external. These multiple perspectives mitigated researcher biases stemming from familiarity with the field and population.

The complementary quantitative findings based on the survey serve as indications only, given the relatively small and disproportional numbers of participants across cases. Another limitation of this component concerns the binary agreement scale regarding benefits from GenAI-DT, which did not allow evaluation of the intensity of participants' agreement. Future research may employ a more granular measure (e.g., a Likert scale) to capture participants' perceptions of GenAI-DT benefits, along with large-scale survey distribution.

6. Conclusion

This research contributes to understanding the dual function of GenAI as both a learning facilitator and a potential learning impediment. The study provides evidence that advances our understanding of how GenAI integration influences cognitive involvement in DT, distinguishing between effective cooperation with GenAI and excessive dependence or cognitive replacement. The results emphasize the need for structured educational frameworks to guide GenAI use, including specific principles for successful GenAI cooperation, metacognitive awareness training, and evaluation methodologies that can distinguish between GenAI-enhanced and GenAI-substituted thinking. This research further demonstrates the consequences of excessive reliance on GenAI, including convergent thinking in early stages and reduced independent reasoning and critical thinking. Based on these findings, we propose an enhanced GenAI-DT process for educators seeking to leverage GenAI's capabilities while preserving critical, creative, and reflective learning outcomes. Our approach builds on existing research suggesting that GenAI systems should emphasize questioning rather than answering to safeguard user autonomy, while incorporating human oversight to preserve emotional and pedagogical integrity (Lu & Hu, 2025). Future studies can examine implementations of the proposed GenAI-DT practices in educational or organizational settings.

Conflict of Interests
The authors declare no conflict of interests.

Data Availability

The survey questionnaire is available at https://drive.google.com/file/d/135I-nmLDyDJr43Ntzx_XReGcifY6bPYr/view.

LLMs Disclosure

Claude.ai was used to enhance language and grammar. Napkin.ai was used to create Figure 1.

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