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Empirical study on problem-solution co-evolution in human-GAI collaborative conceptual design

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Abstract: The problem-solution co-evolution model is a foundational framework for understanding the emergence of creativity in both individuals and teams. With the advent of Generative Artificial Intelligence (GAI), a new paradigm of co-creation in conceptual design has arisen. However, the dynamics inherent to human-GAI collaborations remain largely unknown. In our investigation of the co-evolution dynamics of human-GAI interaction, we employed retrospective protocol analysis to examine the verbal reasoning processes of twenty novice designers co-designing with GAI (text-to-text and text-to-image models). Drawing from the outcomes of our creativity assessments, a key revelation emerged: GAI has the potential to amplify team creativity by fostering human abductive reasoning. In further discourse, we introduce a novel human-GAI co-evolution model, which elucidates the significant role of GAI in aiding human problem-framing exploration. Central to our exploration, we spotlight "introspection" and "retrospection" as pivotal constructs in probing human-GAI collaborations.

Keywords: conceptual design; Generative AI; problem-solution co-evolution; design cognition

1. Introduction

The problem-solution co-evolution model elucidates the mechanism behind the emergence of creativity (Crilly, 2021). Initially inspired by the biological genetic model, co-evolution provided a computational foundation for the exploration of automated design (Maher & Poon, 1996). Subsequently, it evolved into a metaphor for the reasoning process within human design activities, incorporating deeply emotional processes (Dorst & Cross, 2001). Recent insights argue that it offers a precise framework for understanding the development of various interactive systems (Gero et al., 2022).

The evolving landscape of creative teamwork, where GAI transcends its traditional role as a mere facilitator to become a central player, marks a significant paradigm shift in creative collaboration. (Seeber et al., 2020; Figoli, 2022). The conventional co-evolutionary framework has been centered around human cognitive processes in design practices, overlooking the substantial role GAI plays in influencing the evolution of design solutions. Consequently, traditional co-evolution models, primarily based on human-centric paradigms, require reexamination and adaptation to encapsulate the nuanced interaction between humans and GAI in the problem-solution co-evolution process.

To investigate novel mechanisms of human-GAI co-evolution, conceptual design was selected as the research domain due to its significant creative potential during the design process (Figoli, 2022). The study is guided by the following inquiries:

- RQ1: Given that design hinges on the reasoning processes of individuals and teams (Rittel, 1987), how does GAI influence alterations in human reasoning patterns?

In response, a retrospective protocols study was conducted, employing text-to-text and text-to-image GAI models (ChatGPT and Midjourney) to examine human verbal reasoning in scenarios with and without GAI support. Through qualitative protocol analysis, the study analyzed reasoning pattern distribution in human-GAI collaborations.

- RQ2: Identifying the principles of co-evolution, delineating key practices propelling this process, and developing corresponding methods and tools represent challenges in design research (K. Dorst, 2019). What constitutes essential practices in human-GAI collaboration?

This question was addressed by gauging the creativity level manifested in human-GAI collaborations through expert assessments. By scrutinizing the interplay and causality among creativity scores, GAI outputs, and human abductive reasoning, the study sheds light on crucial methodologies in human-GAI collaborative efforts.

- RQ3: Within the ambit of human-GAI collaboration, how has the problem-solution co-evolution model evolved?

Building on the theoretical underpinnings established by our predecessors and the insights derived from our research, we present a human-GAI co-evolution model. This model elucidates the macro-reasoning process inherent in human-GAI collaboration, shedding light on the influence of GAI on human cognition.

The human-GAI co-evolution model highlights the necessity and motivation for humans to develop rational frameworks via collaboration with GAI. It accentuates the importance of continuous reflection in action for sustaining effective co-evolution, or "knowledge in motion" (Magnani, 2017). To enhance the multi-level human-GAI co-evolution model, future studies should strive to incorporate a broader and more diverse pool of participants. This approach will validate and extend the applicability of the cognitive and reasoning patterns observed.

2. Literature review

2.1 Human-AI collaboration in complex design environments

Human cognitive models and AI computational models have demonstrated complementary strengths in design cognitive perspectives, with depth-first search and breadth-first search showing performance advantages in their respective design search processes (Maher, M., 2003). Contemporary design practices are shaped by diverse socio-cultural, socio-economic, and environmental contexts (Rampino, 2018). With the growing complexity of design environments, designers are increasingly incorporating AI, specifically GAI, to augment every phase of the design process (Figoli, 2022). Recent research has underscored GAI's role as a co-creator in design, offering significant potential for innovation (Gmeiner et al., 2023).

A transformative shift is occurring in the dynamics of creative teams, where the distinction between humans and GAI is increasingly becoming blurred. GAI is evolving from a tool that merely enhances performance to an active contributor within teams (Seeber et al., 2020). This evolution has led to the formation of teams composed of both humans and GAIs, introducing new dynamics in teamwork (Figoli, 2022). To address potential side effects of GAI integration (Possati, 2020), emphasis should not only be placed on GAI's performance but also on its impact on designers' cognitive processes, thus facilitating a deeper understanding of their mental frameworks.

2.2 Integration of GAI in conceptual design

In recent years, the advent of GAI models, including ChatGPT and Midjourney, has transformed the landscape of conceptual design. These models excel in a broad spectrum of tasks, from answering general inquiries to generating complex images, opening new pathways in the design field (Gozalo-Brizuela & Garrido-Merchan, 2023).

Large Language Models (LLMs) possess a remarkable ability to understand and process natural language, offering invaluable assistance to designers at the initial stages of concept generation. Their strength lies in absorbing extensive textual data, including manuals, technical specifications, and academic papers, allowing them to address questions with this integrated knowledge (Stella et al., 2023). From this LLM framework, a variety of text-to-text tools have emerged.

A prime example of GAI's potential is seen in collaborations between ChatGPT and designers on robotic design projects (Stella et al., 2023). This cooperative strategy extends beyond traditional human learning boundaries, fostering effortless exploration of interdisciplinary collaboration and promoting comprehensive research. Nonetheless, incorporating LLM into the design process presents challenges and raises questions for further inquiry, especially regarding its effectiveness in the complex design environment.

Furthermore, various text-to-image GAI models have demonstrated their ability to augment early concept design by providing visual inspirations and diverse stimuli (Kwon et al., 2023). These tools enable rapid iterations and broad exploration, allowing designers to accurately convey and visualize their conceptual ideas. Leading models such as Midjourney, DALL-E 2, Stable Diffusion, IMAGIN, and Muse have been developed.

2.3 Reasoning in designers' dynamic mental models

The role of the designer is dynamic, necessitating ongoing exploration to enhance design strategies. There exists a potential risk that the model-based reasoning of GAI may not align with the designer's mental model, potentially housing distinct decision-making processes (Pauwels, P. & Singh, V., 2021).

Reasoning originates from mental models, with its outcomes conforming to particular mental constructs (Johnson-Laird, 1999b). The rationale behind design has predominantly been conceptualized from logical standpoints, incorporating abductive, deductive, and inductive reasoning (Dorst, 2011; Roozenburg, 1993). Among these forms of reasoning, abductive reasoning plays a crucial role in generating new ideas, positioning it as the foremost type of reasoning in design activities (Dorst, 2011; Roozenburg, 1993). Characterized by a reverse-thinking approach, abductive reasoning progresses from envisaging the desired outcome to understanding its causation (Dorst, 2015). This approach is evident in the co-evolution concept in design, wherein designers alternate between interpreting the problem and identifying potential solutions until an innovative alignment is reached (Dorst & Cross, 2001).

2.4 Problem-solution co-evolution model in Human-GAI collaboration analysis

Co-evolution represents a complex concept that encapsulates the evolution of interdependent systems. It has been pivotal in elucidating developmental trajectories across diverse domains (Gero & J., 2022). The problem-solution co-evolution model emphasizes the symbiotic relationship between speculative problem domains and solution spaces, delineating both horizontal and diagonal developmental paths. However, the details of this relationship are still not fully understood. Maher et al.'s (1996) model (Figure 1) distinguishes between goal-oriented search behaviors and explorations not directed by specific goals. In contrast, Cross and Dorst's (2001) model (Figure 2) places a greater emphasis on problem framing, concentrating on the symbiotic interaction between problem and solution domains.

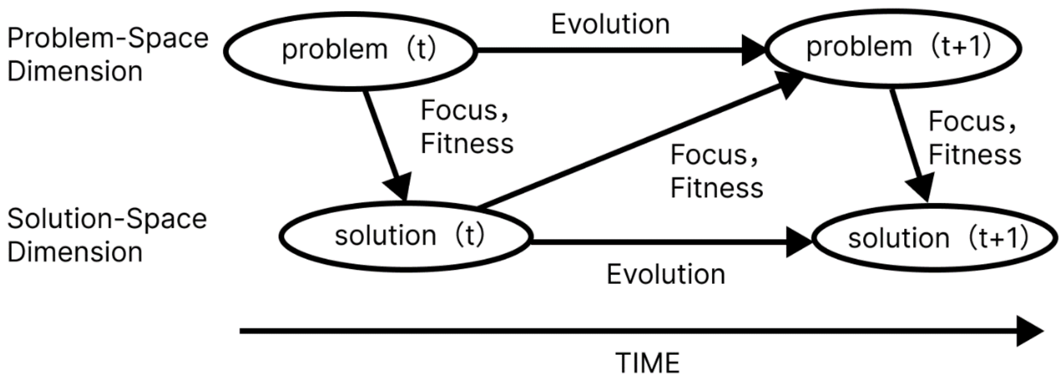

Figure 1 The co-evolution model of Maher et al. (1996)

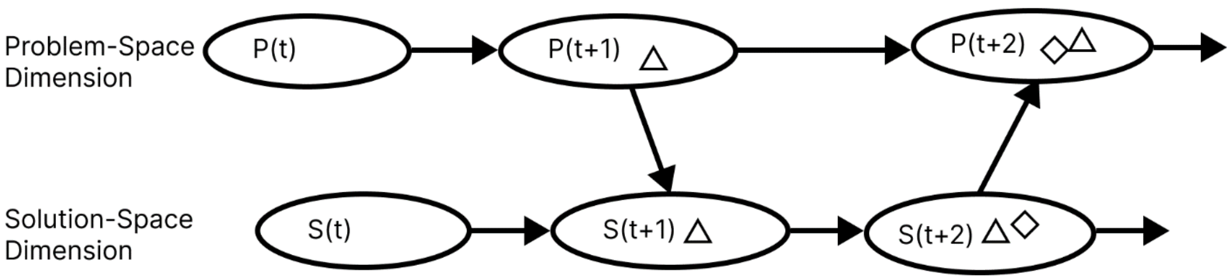

Figure 2 The co-evolution model of Cross et al. (2001)

Artificial Intelligences transcend their engineered nature, functioning as social actors characterized by unique behavior patterns (Possati, 2020).Historical co-evolution models have largely overlooked the role of GAI. Acknowledging this gap, the emerging paradigm of human-GAI collaborative design aims to investigate human reasoning in the context of GAI collaboration, establishing a foundation for deeper understanding of effective human-GAI co-creation.

3. Methods

In our research, we utilized a qualitative protocol analysis approach to investigate the reasoning processes in human-GAI collaboration (ChatGPT 3.5 and Midjourney). Data was collected using retrospective protocols, with the problem-solution co-evolution model as the analytical framework for the data obtained. This paper details the rationale for this methodological choice and provides a summary of relevant findings from related studies. As illustrated in Figure 3, there is a direct correlation between the methods used and the research questions posed.

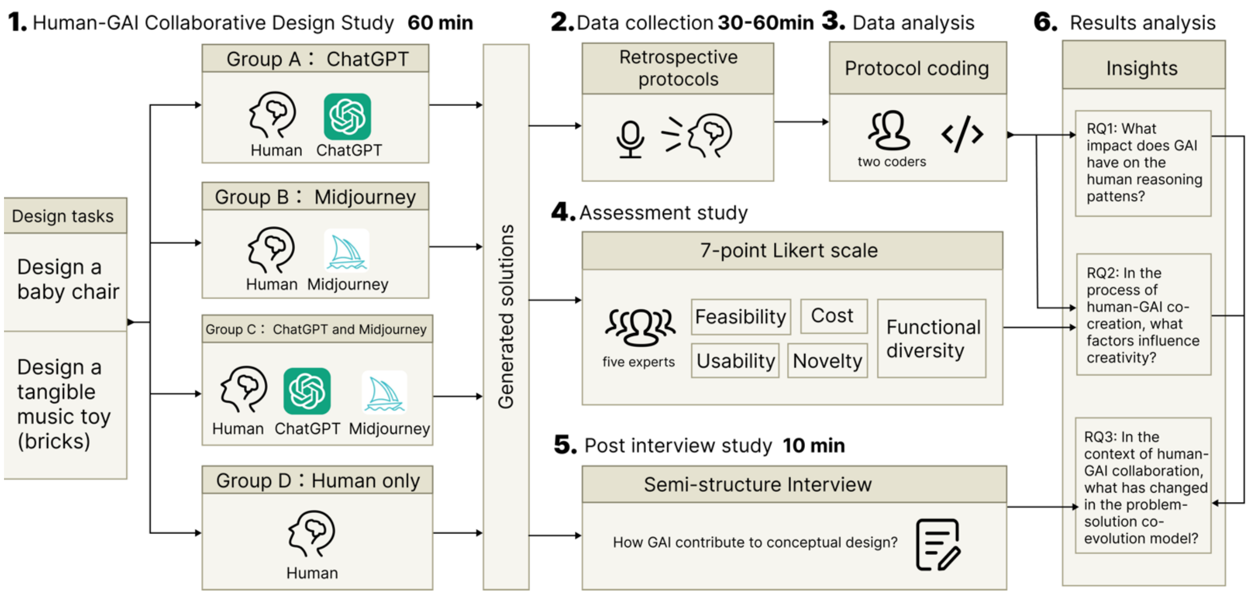

Figure 3 The study protocol

3.1 Protocol: Human-GAI collaborative design study

The study recruited twenty participants, consisting of thirteen females and seven males, with an average age of 24 years. All participants were majoring in design, including nineteen in their first or second year of graduate studies and one in their final year of undergraduate studies.

The selection of Text-to-text and Text-to-image models from the extensive range of GAI models was strategically made to propel the development of multimodal GAIs aimed at enhancing design processes. In identifying exemplary GAI tools for the study, specific criteria were established. Firstly, the GAI tool must be commercially available, indicating its maturity and stability within the GAI ecosystem. Secondly, the tool should provide a clear, well-organized, and user-friendly interface to ensure seamless interaction. Adherence to these criteria guarantees the reliability of the selected tools and reduces external influences on the study's outcomes. Consequently, ChatGPT3.5 was chosen as the representative for Text-to-text GAI tools, and Midjourney was selected for Text-to-image GAI tools.

All participants willingly joined the study, driven by their interest in the research topic, familiarity with ChatGPT and Midjourney, and their relatively comparable design skill sets. The study involved two distinct conceptual design tasks to mitigate bias that could occur from completing a single task.

- Task 1: Design a baby seat in 30 minutes.
- Task 2: Design a tangible musical block in 30 minutes.

Both tasks, drawing inspiration from winners of the Red Dot Concept Design category, required a seamless integration of elements from ergonomics, engineering, aesthetics, and interaction. The baby seat design task focused on user-centric considerations, providing ample opportunities for innovative solutions in functionality and material selection. Conversely, the tangible musical toy task presented participants with the challenge of possessing technical expertise, understanding music theory, and adopting a creative approach to defining the problem.

Participants were randomly allocated into four groups: three experimental groups (A, B, C) and one control group (D), with five participants in each group. The following outlines the specific requirements designated for each group:

- Group A: Participants were asked to complete two design tasks using ChatGPT.
- Group B: Participants were asked to complete two design tasks using Midjourney.
- Group C: Participants were asked to complete two design tasks using ChatGPT and Midjourney, but were not instructed on the order in which the two GAI tools should be used.
- Group D: Participants were asked to complete both tasks without GAI assistance.

Prior to the initiation of the design tasks, participants received a concise tutorial on utilizing ChatGPT and Midjourney Prompt for generating conceptual designs. Following the tasks, participants showcased their design concepts, either through descriptive text or illustrative images.

The current study employs a retrospective cued recall (RCR) method, which is grounded in the principles of action-reflection (Schön, 1984), to reconstruct participants' actions, rationales, emotional reactions, and responses to recorded events (Russell & Chi, 2014). This approach not only captures the inherent cognitive behaviors but also aims to understand a designer's perception, visualization, and the challenges encountered within the design context, leveraging the well-established human capacity to visually recognize and comment on previously encountered scenarios (Russell & Chi, 2014; Suwa et al., 1998; Suwa et al., 2004).

Retrospective recall is favored to avoid disruption during the problem-solving process and to capture a broader range of metacognitive information, allowing designers to work unimpeded and subsequently analyze their sessions via video recordings (Van et al., 2005; Maher & Tang, 2003a). The records for Groups A, B, and C include the prompts used by humans and the outputs generated by GAI. These sessions were then transcribed, with times ranging from 30 to 60 minutes, documenting the cognitive processes of participants and highlighting their action-reflection cycles within the design process.

Following the design phase, semi-structured interviews were conducted. During these interviews, participants discussed the contributions of GAI to their designs and described the collaboration between the designer and GAI. Each interview lasted approximately 10 minutes.

3.2 Protocol coding

In human teams, abduction serves as the principal mechanism for generating new ideas and facilitating the co-evolution of problem and solution spaces (Cramer-Petersen et al., 2019; Cash, P. et al., 2023). Our coding methodology is designed to explore whether, in teams composed of both humans and GAI, induction and deduction could also act as reasoning methods that advance the co-evolutionary transition of problems and solutions under the influence of GAI.

Transcripts were analyzed with a focus on two main variables: co-evolution transitions and types of reasoning, to clarify the collaborative dynamics between humans and GAI in the context of co-evolutionary design. The criteria for segmentation were determined by the transitions in co-evolution. The coding procedure was divided into two phases, as depicted in Figure 4.

Figure 4 Protocol coding

In the protocol coding methodology, data collection commences with prompts, outputs, records, and retrospective protocols, subsequently processed as qualitative data. The data analysis phase employs the NVIVO tool for analysis, organizing the data into an affinity diagram. This organized data is encoded using descriptive and interpretive coding techniques, leading to the identification of four primary categories: Problem-Problem, Problem-Solution, Solution-Problem, and Solution-Solution. This process also uncovers three new codes: Abduction, Deduction, and Induction. Thematic analysis is applied to assess the data's supportiveness, achieve consensus, and verify the diversity of examples. The ultimate objective is to understand the influence of GAI on human reasoning patterns and to clarify the contribution of abductive reasoning in human-GAI collaborative design.

The coding criteria for co-evolution transitions were adapted from Cash et al. (2023), building on earlier research (Becattini et al., 2015; Maher & Poon, 1996): (Seeber et al., 2020)

- Problem-Problem(P-P): Horizontal transitions in the problem space, referring to problem decomposition, definition, and refinement of goals and requirements.
- Problem-Solution(P-S): Diagonal transition from problem to solution space, referring to the exploration of possible ideas appropriate to understanding the problem at a given moment. The starting point for this transition is the current problem definition, requirements or goals.

- Solution-Problem(S-P): Diagonal transition from solution to problem space, referring to when ideas trigger a change or reframing of the understanding of the problem.
- Solution-Solution(S-S): Horizontal transitions in the solution space, referring to the synthesis and elaboration of the solution (or parts of it) S-S shifts begin with previously created ideas that are further refined.

The coding approach to analyzing the reasoning process is derived from the work of Cramer-Petersen et al. (2019), which presents an empirical method for examining the reasoning process in research design. Attempts at verbal reasoning are deemed effective due to their resemblance to formal reasoning processes (Perelman et al., 1971). A prevalent explanation within cognitive science posits that beliefs and knowledge contained within mental models, which are employed to deliberate on a specific task or event, are retained in working memory, enabling their clear articulation (Christensen & Schunn, 2009). The coding methodology for categorizing types of reasoning is detailed in Table 1.

Table 1. Reasoning type and definitions for coding and Reasoning indicator words.

Reasoning type	**Coding definitions**	**Indicator words**
Abduction	• A hypothesis or assumption to account for what is observed or what is desired or intended • Creating ideas (to a problem) from imagination • A belief held without proof or certain knowledge • Preliminary guess to introduce hypotheses	could, maybe, think, could be, imagine, probably, likely
Deduction	• Definitive and certain conclusion • Explicating hypothesis by suggested consequences • Prediction of result in a given frame • Proves something must be • Explores consequences of an abduction	so, then, therefore, that is, must be, as, can
Induction	• Tests a hypothesis with available data (predictions) • Generalises from specific instance or idea • Evaluates if something is operative • Inferring from observed to unobserved • Inferring about future courses of events	I, me, you, they, we, them

3.2 Assessment study protocol

Five design experts (consisting of three males and two females, aged 25-29) with at least five years of experience in design research were recruited to evaluate the effectiveness of human-GAI collaborative co-evolution in design. Their main responsibility was to assess the creativity of 40 conceptual design solutions generated by participants in the human-GAI collaborative design. For comparison, two reference concepts from the Red Dot Award, namely the "Smart Baby Carrier R041" and the "Animal World - Domino Piano", were selected as benchmarks. These references were crucial for establishing a uniform assessment framework.

The experts reviewed the 40 design solutions and were asked to rate them on a 7-point Likert scale (with 1 representing 'very poor' and 7 indicating 'excellent'). The evaluation criteria included novelty, feasibility, usability, functional diversity, and cost. This assessment session lasted for about 30 minutes. The selection of criteria was guided by Ulrich et al.'s (2008) parameters for measuring creativity in conceptual design.

4. Result

In this section, we demonstrate that the choice of GAI tool (ChatGPT, Midjourney, or a combination of both) has a direct impact on human reasoning patterns. These modified reasoning patterns, particularly the enhanced role of abduction in idea generation, subsequently affect the overall creativity of design outcomes. White (2023) suggested that creative abduction bridges the gap between the current input with its associated internal dynamics (problematic) and the ideal input with its related internal dynamics (non-problematic), highlighting the importance of this process in tackling pressing issues: creative abduction provides avenues to navigate these challenges. We propose the perspective that abductive reasoning acts as a pivotal mediator in this interaction. GAIs, especially Midjourney, may exert varied direct effects on creativity; however, when their influence on abductive reasoning is accounted for, their impact on creativity becomes significantly clearer and more profound.

4.1 Impact of Human-GAI collaboration on human reasoning patterns

To address Research Question 1 (RQ1), two coders analyzed four co-evolution transitions and three inference behaviors using retrospective protocols. To ensure the reliability of the coding, approximately 10% of the data was cross-referenced. The kappa coefficient for intercoder reliability was calculated for each code, demonstrating consistently satisfactory reliability.

Co-evolution transitions were classified into four distinct types, establishing the basis for our transcript segmentation. Each segment represented a co-evolution transition, serving as a fundamental unit in the design process and a critical element of our analysis. This approach yielded a total of 686 segments. Notably, within these segments, multiple inference behaviors were observed, totaling 1322 identified inference behaviors. Figure 5 depicts the distribution of human reasoning across the four groups.

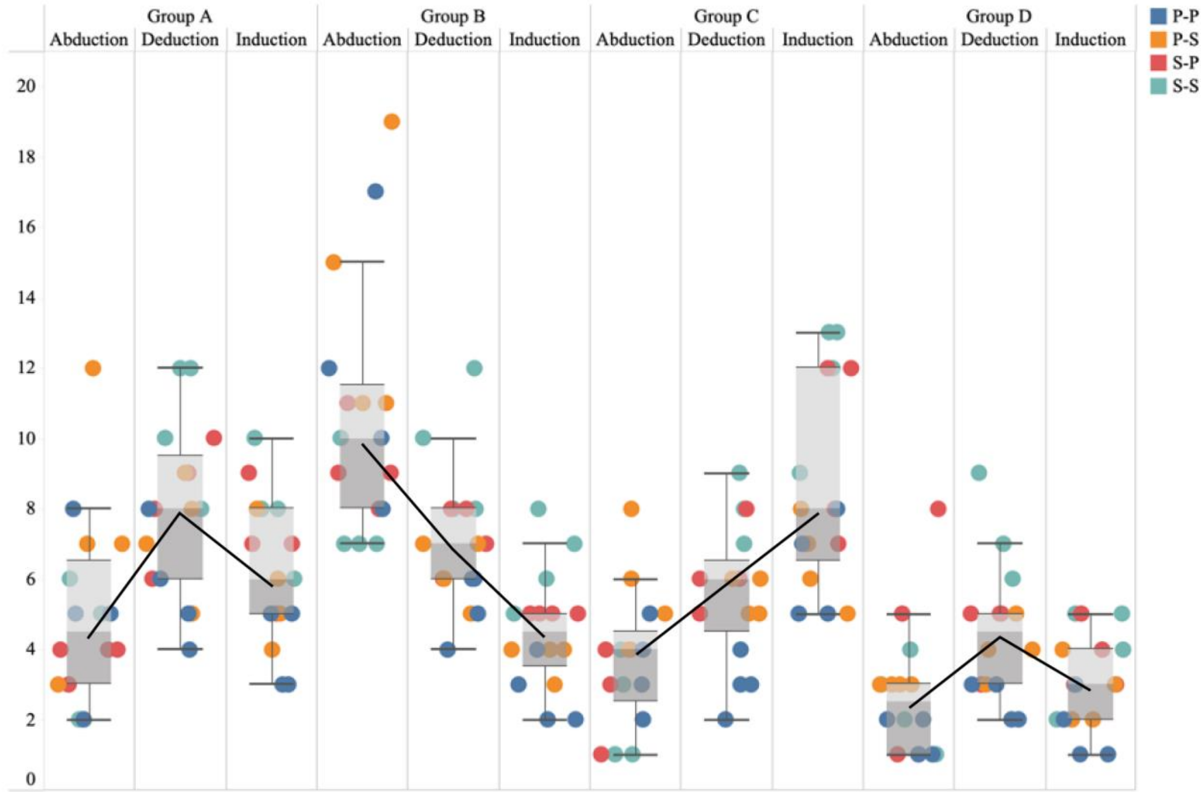

Figure 5 Distribution of human three reasoning types

The chart presented combines box plots and scatter plots to offer insights into the impact of various GAI tools—specifically ChatGPT, Midjourney, a combination of both, or the absence of any—on the three reasoning methods (abduction, deduction, induction) employed during the design processes.

In Group A (ChatGPT), the reasoning pattern closely aligns with that of the control group (Group D), featuring a significant emphasis on abduction, indicative of its capacity to foster new ideas, yet the overall reasoning pattern mirrors that observed in Group D. Group B (Midjourney) shows a notable prevalence of abduction, suggesting Midjourney's potential to activate diverse reasoning modes in the idea generation phase. In Group C (ChatGPT and Midjourney combined), a pronounced synergistic effect emerges, with induction being particularly prominent, implying that the primary human role involves idea evaluation. In Group D (no GAI tools), there is a distinct shift towards deduction, highlighting that without the influence of GAI, teams may lean more towards refining existing ideas rather than generating new ones.

For a deeper understanding of the data, specific examples are provided in the following sections (Table 2). For clarity, examples from Group C have been translated from Chinese to English. The example illustrates that abduction predominantly directs the co-evolutionary transformation of problems and solutions in human-GAI collaboration. However, in Group C, the Solution-Solution and Problem-Solution evolution can be influenced by induction and deduction, indicating that GAI may assume a pivotal role in the human-GAI collaborative process.

Table 2. Example of co-evolution transitions in Group C protocols

Segment	**Co-evolution transitions**	**Reasoning type**
“Mainly because the product of stroller and baby seat has such a special user group. Babies are a group that we generally don’t fully understand in our common sense. The requirements it provides here are too common.”	P-P	Induction Abduction
“In fact, this means that he just gave some options, but the designer needs to make subjective changes in how to combine them. Then I also described to him the shape I wanted.”	S-S	Deduction Abduction
“So when it comes to materials, there should be two aspects. On the one hand, the quality generated by the description of material will be much more accurate.”	S-S	Deduction Abduction
“The material doesn't look very appropriate, and the surface treatment is definitely not right, which won't be very expressive.”	S-P	Deduction Abduction Induction
“I'll give it the words "feasible" first. I'm not sure if this will work, but you can give it a try.”	S-S	Deduction Abduction
“So we should put “portable” here and into this keyword.”	S-S	Deduction
“This word that would make his design category ambiguous is not needed, and the words modern, brand, and identity are also not needed.”	P-S	Deduction Induction
“Because if you look at this thing now, it is obvious that it is greatly influenced by the word chair. It's too detailed, and it's impossible to control it in the prompt.”	S-P	Deduction Induction Abduction

4.2 Creativity assessment results

Figure 6 illustrates the distribution of Likert scale responses related to creativity scores as evaluated by experts. Table 3 presents the Cohen's kappa for the experts, with an average value of 0.66, indicating a satisfactory level of agreement among them. The analysis demonstrated that the creative output of the Human-GAI team, specifically when assisted by Midjourney (average of five metrics = 4.336, SD = 1.62), exceeds that of teams assisted by ChatGPT (average of five metrics = 4.236, SD = 1.41), outperforms the combined efforts of ChatGPT, Midjourney, and human teams (average of five metrics = 4.1, SD = 1.54), and is significantly higher than that of individual human design efforts (average of five metrics = 3.588, SD = 1.27).

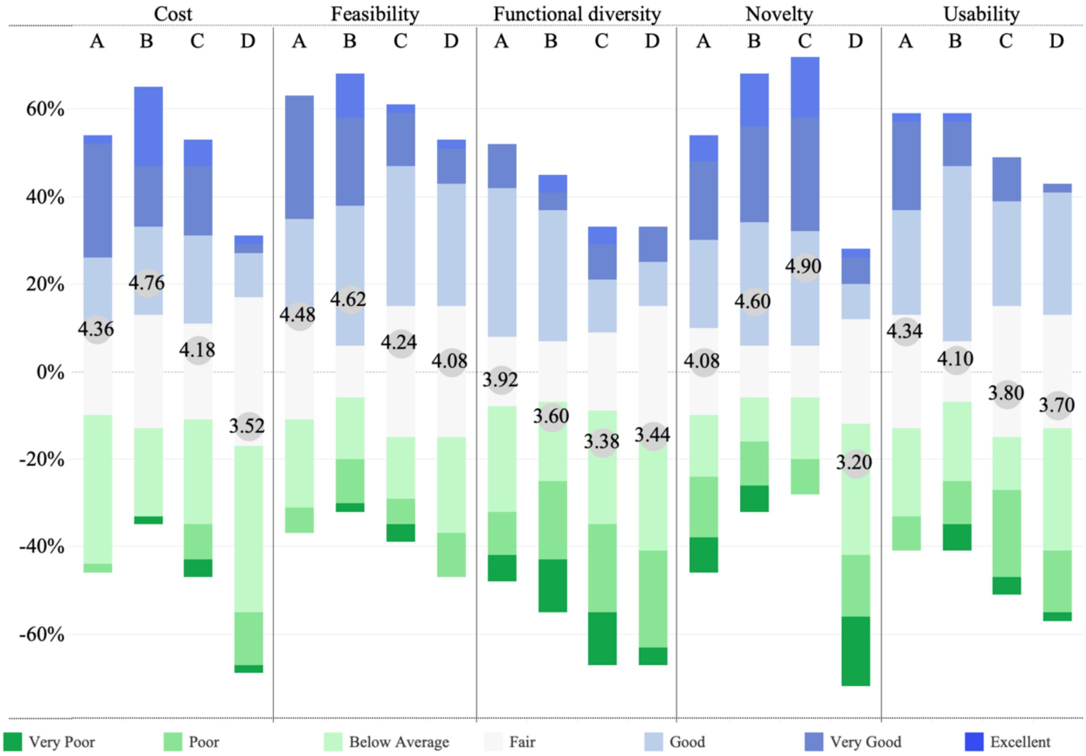

Figure 6 Distribution of Likert scale responses on the creativity score of 4 groups

Table 3. The Cohen's kappa results

	Experts 1	**Experts 2**	**Experts 3**	**Experts 4**	**Experts 5**
Experts 1	/				
Experts 2	0.72	/			
Experts 3	0.78	0.92	/		
Experts 4	0.52	0.72	0.78	/	
Experts 5	0.37	0.58	0.64	0.55	/

When humans collaborate simultaneously with two types of GAI models, the assessed levels of creativity seem to be lower compared to collaboration with just one GAI model, particularly in the dimensions of functional diversity, feasibility, and usability. This outcome was unexpected for us. Therefore, by incorporating protocol analysis of human reasoning processes, we initiated a further review to comprehend the underlying reasons for this observation.

4.3 Factors influencing creativity in Human-GAI collaboration

Abduction remains a distinct human capability, setting us apart from AI (Pauwels, P. & Singh, V., 2022). Using stepwise regression, we compared four different groups (with Group D as the reference) to explore the relationship between abduction and creativity scores, thereby addressing Research Question 2 (RQ2).

Table 4 presents the effect of GAI on the Creativity Score. For the group utilizing ChatGPT (Group A), the Creativity Score increases by 0.648 units compared to the group without any GAI tool (Group D), a significant effect at the 5% level. For the group employing Midjourney (Group B), there is an increase of 0.748 units in the Creativity Score relative to Group D, significant at the 1% level. For the group using both ChatGPT and Midjourney simultaneously (Group C), the Creativity Score rises by 0.512 units compared to Group D, with significance at the 10% level.

Table 5 details the impact of GAI on Abductive Reasoning. Group A exhibits an increase in abductive reasoning by 7.2 units over Group D, statistically significant at the 10% level. Group B shows a notable advantage of 27.2 units in abductive reasoning over Group D, significant at the 1% level. The difference in abductive reasoning between Group C and Group D is not statistically significant.

Table 6 explores the Combined Influence of GAI and Abductive Reasoning on Creativity Score. Considering the impact of abductive reasoning, the gap in Creativity Score between Group A and Group D reduces to 0.230 units, remaining significant at the 10% level. Group B's Creativity Score is lower by 0.833 units compared to Group D, a disparity that is significant at the 1% level. The difference in Creativity Score between Group C and Group D is 0.245 units, significant at the 10% level. Abductive reasoning significantly enhances the Creativity Score; with each unit increase in abductive reasoning, there is a rise of 0.058 units in the Creativity Score, highly significant at the 1% level.

Table 4 Stepwise regression coefficient test: The impact of GAI on Score.

Creativity Score	**Coefficient**	**SD**	**t**	**P>t**	**[95% conf.**	**interval]**
A	0.648**	0.246	2.63	0.018	0.127	1.169
B	0.748***	0.246	3.04	0.008	0.227	1.269
C	0.512*	0.246	2.08	0.054	-0.009	1.033
cons	3.588***	0.174	20.63	0	3.219	3.957

Note: ***, **, and * indicate that the corresponding coefficients are significant at the 1%, 5%, and 10% levels respectively, the same below.

Table 5 Stepwise regression coefficient test: The impact of GAI on Abduction.

Abduction	**Coefficient**	**SD**	**t**	**P>t**	**[95% conf.**	**interval]**
A	7.2*	3.767	1.91	0.074	-0.786	15.186
B	27.2***	3.767	7.22	0	19.214	35.186
C	4.6	3.767	1.22	0.24	-3.386	12.586
cons	10.6***	2.664	3.98	0.001	4.953	16.247

Table 6 Stepwise regression coefficient test: The impact of GAI and Abduction on Score.

Creativity Score	**Coefficient**	**SD**	**t**	**P>t**	**[95% conf.**	**interval]**
A	0.230*	0.128	1.79	0.094	-0.044	0.503
B	-0.833***	0.239	-3.48	0.003	-1.342	-0.323
C	0.245*	0.121	2.02	0.062	-0.013	0.503
Abduction	0.058***	0.008	7.56	0	0.042	0.075
cons	2.972***	0.116	25.72	0	2.726	3.218

In summary, compared to the group that does not use any GAI tool, employing a GAI can enhance the Creativity Score, with Midjourney showing the most significant effect. Midjourney notably supports abductive reasoning. However, when considering the impact of abductive reasoning, Group B's Creativity Score is lower than that of Group D. This indicates that Midjourney's direct influence on the Creativity Score might be negative, but it positively affects the Creativity Score by enhancing abductive reasoning. Another possibility is that retrospective protocols may introduce additional cognitive processes that support abduction.

5. Human-GAI co-evolution modeling

Drawing on our empirical analysis of human-GAI collaboration, we have developed a model of the collaborative process to address Research Question 3 (RQ3). A growing area of interest within the GAI field focuses on achieving causal reasoning. Building on the problem-solution co-evolution model proposed by Maher (1996), we introduce a new concept: the solution space of the machine, as illustrated in Figure 7.

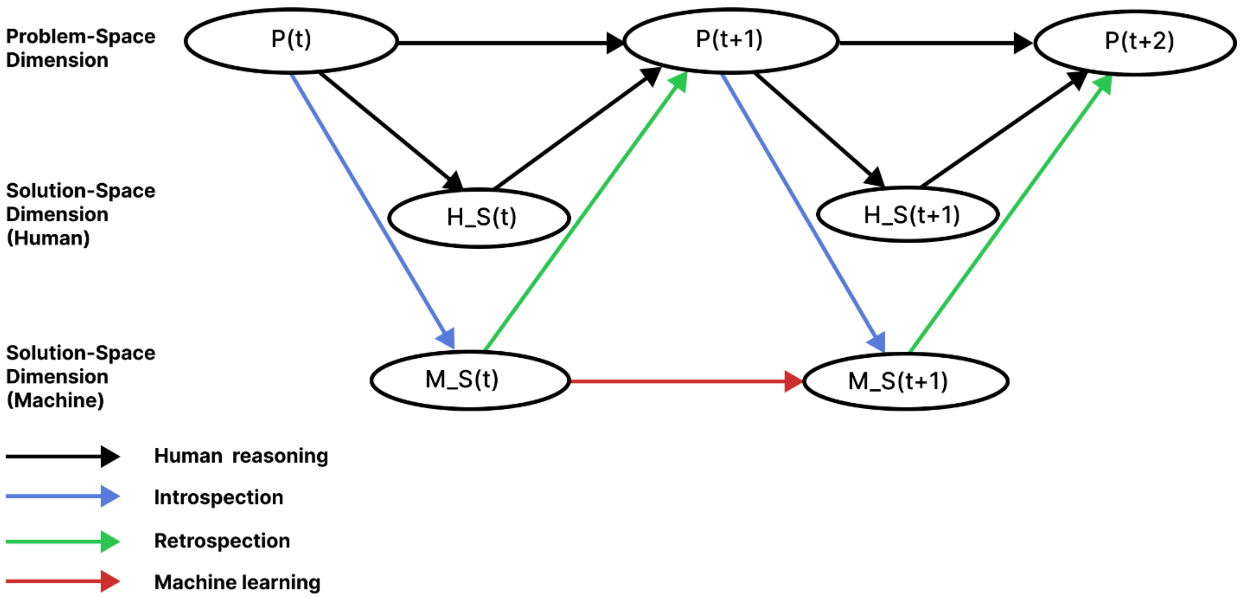

Figure 7 Human-GAI co-evolution model.

The model delineates the co-evolution of humans and GAI across a timeline, illustrating the interaction between the human problem space P(t) and the solution spaces of both humans H_S(t) and GAI M_S(t), and their progression over time to P(t+1) and P(t+2).

Initially, the model presents two dimensions: one for the problem space and another for the solution space. The problem space dimension is linear, reflecting the sequential nature of problems evolving over time. Conversely, the solution space dimension divides into human and GAI pathways, demonstrating how both entities independently tackle problems at any given moment.

The model highlights three key processes: introspection, retrospection, and machine learning:

- Introspection: This process embodies the human tendency to seek GAI assistance when facing a problem and the need to develop identification logic (Possati, 2020). It is a vertical process, moving directly from the problem space P(t) to the GAI solution space M_S(t), indicating human reliance on GAI for solutions or recommendations.
- Retrospection: The transition from GAI's solution space M_S(t) back to the problem space P(t+1) indicates that after receiving a solution from GAI, humans revisit the problem, possibly making modifications or adaptations at the next time point. This reflects human "reflection in action" (Schön, 1984), merging GAI suggestions with human needs and constraints, and represents a process of creative abduction, generating "knowledge in motion" (Magnani, 2017).
- Machine learning: GAI extends beyond providing solutions; it continuously learns. As it moves from M_S(t) to M_S(t+1), GAI refines its understanding by analyzing human decisions and solutions, thereby continuously evolving.

By analyzing AI as a distinct type of actor characterized by specific behavioral patterns and ecology (Possati, 2020), this model provides a structured methodology for considering the collaboration between humans and GAI in design and problem-solving contexts. It highlights the dynamic interaction between the two, illuminating their co-evolution over time.

6. Conclusion

In the realms of design studies and human-computer interaction (HCI), grasping the collaborative dynamics between humans and GAI is pivotal for the enhancement of design methodologies and technological advancements. Our investigation enriches this dialogue by introducing a novel reflective aspect in the human-GAI co-evolution model, informed by human propensities for identification, reasoning, and engagement with intelligent systems (Possati, 2020). This reflective capability is crucial in design endeavors where GAI's role is dynamically adaptive, bolstering the team's capacity to innovatively confront and overcome design obstacles.

Our results indicate that GAI can provoke abductive reasoning in humans, leading to heightened creative outcomes. However, when GAI overshadows the problem-solving process, sidelining human abductive reasoning, creativity tends to wane. This finding holds substantial implications for HCI by implying that GAI tool design should aim to augment and support human cognitive functions rather than supplant them.

Practically, this research prompts HCI professionals to deliberate on the structuring of GAI tools and workflows to cultivate a mutually beneficial relationship with users. To conclude, this study provides preliminary insights into the co-evolution of human-GAI interaction within the design sphere. Acknowledging the limitations of a small, uniform sample, this investigation lays groundwork for future, more expansive studies. A discernible gap exists for research that spans a wider array of disciplines, cultures, and demographic backgrounds to thoroughly understand the effects of human-GAI cooperation.

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