Deconstructing the Designer-genAI Interaction in the Design Process: A Framework for Surfacing Micro-Dynamics and Agency

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Deconstructing the designer-genAI interaction in the design process: A framework for surfacing micro-dynamics and agency

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Abstract: This paper presents the Imagery Modes framework for analysing the designer–genAI interaction, complementing established metaphor-based accounts. Developed through Constructivist Grounded Theory and structured using Activity Theory, the framework focuses on the micro-dynamics of a single input–output exchange. It identifies four sequential sub-actions—crafting, processing, generating, and evaluating—that trace the relations between subjects (designer, genAI) and instruments (input, output). Central to the framework is the concept of "output imagery", defined as the clarity with which the designer envisions the expected output prior to the interaction. Three modes of interaction are identified: Before, During, and After Imagery. The findings highlight the fluid and non-linear character of the designer-genAI interaction, showing how designers shift between modes across sequences. Finally, the framework clarifies the interplay between agency and sense of agency, showing that while agency varies linearly, sense of agency depends on alignment between expectations and outputs within each mode.

Keywords: Human-AI Interaction; Generative AI (genAI); Interaction Patterns; Agency and Sense of Agency

1. Introduction

In recent years, Artificial Intelligence (AI) has become increasingly embedded across professional domains, leading some scholars to describe the present moment as an "AI revolution" (Makridakis, 2017; Miailhe & Hodes, 2017). Although adoption is accelerating, its broader societal implications are expected to unfold gradually (Makridakis, 2017), positioning the early 2020s as a transitional phase marked by technological momentum and uncertainty. Design, as a field inherently responsive to socio-technical change (Rampino, 2022), is deeply involved in this transition. Within this context, generative AI (genAI) has introduced both opportunities and concerns, from the expansion of creative possibilities (Wilson & Daugherty, 2018) to debates around authorship (Draxler et al., 2024), deskilling (Bankins & Formosa, 2023), and environmental impact (George et al., 2023).

As genAI becomes more integrated into design workflows, it challenges established assumptions about the designer's role (Verganti et al., 2020) and has prompted growing academic attention (Abbasi et al., 2024). At the same time, the rapid evolution of genAI makes it difficult for academic inquiry to stabilise concepts and identify coherent trajectories (Figoli et al., 2025). Within this evolving landscape, three orientations are particularly relevant for the present inquiry into designer–genAI interaction: (i) the predominance of metaphorical framings, such as AI being described as "assistant", "collaborator", or "agent", to characterise designer–genAI relations (van der Maden et al., 2025), which, while useful, may benefit from complementary accounts; (ii) The limited attention to the micro-dynamics of designer–genAI exchanges, as existing frameworks typically operate at the level of extended processes or overarching models and thus overlook what unfolds at the finer scale of single exchanges; (iii) the underexplored relationship between agency (i.e., the actual capacity to influence a process) and sense of agency (i.e., the subjective perception of having influence), which remains largely unaccounted for in existing accounts of designer–genAI interaction.

This paper addresses these issues by introducing an analytical lens grounded in empirical data from practitioners who use genAI in their design work. It makes three contributions. First, it decomposes a single designer–genAI input–output cycle into four empirically derived sub-actions and synthesises them into a conceptual visualisation. Second, it develops the Imagery Modes Framework, identifying three modes of interaction based on the degree of output imagery definition. Third, it clarifies how agency and sense of agency vary across these modes. This reframing offers a refined perspective on the relational dynamics between designer and genAI, contributing intermediate-level knowledge (Höök & Löwgren, 2012) that supports both scholarly reflection and professional practice.

2. Related works

2.1 Metaphors in human-AI research: Opportunities and limits

Research on designer–genAI interaction builds on the established field of human–computer interaction (HCI), drawing on concepts developed for earlier computing systems. For example, discussions on computers as creative partners (Lubart, 2005) have regained relevance in the context of genAI.

Among the most enduring inheritances from HCI is the use of metaphors to render complex systems intelligible (Blackwell, 1996; Murray-Rust et al., 2022; Sengers et al., 2005). In AI studies, metaphors help articulate system functions, boundaries, and expectations. As Lupetti and Murray-Rust (2024) observe, even the term "artificial intelligence" prompts metaphorical attributions of human qualities, such as thought, imagination, memory, or intention (Cho et al., 2023). Similarly, machine-learning discourse frequently employs metaphors such as "training," "learning," and "black box" to translate technical processes into more accessible language (Murray-Rust et al., 2022).

However, the very strengths of metaphors may also introduce risks. As linguistic shortcuts (Connell, 2019), they may obscure complexity and carry unexamined assumptions into new domains (Murray-Rust et al., 2022), which is especially problematic in relation to genAI, systems already marked by inherent opacity (Karras et al., 2021). They may also not be neutral. Lupetti and Murray-Rust (2024), for instance, highlight how AI discourse often borrows supernatural imagery, such as “spellcasting,” “alchemy,” and “invoking” (Derczynski, 2023), mystifying its inner workings. In this light, noticing and selecting helpful metaphors may become a challenge for both researchers and practitioners (Murray-Rust et al., 2024).

In early AI and creativity research, metaphor-based classifications were often used to describe system roles in creative processes—functional roles such as “support” or “generator” (Maher, 2012), behavioural roles such as “pleasing” and “provoking” (Kantosalo & Toivonen, 2016), and characterisations like “nanny”, “coach”, or “colleague” (Lubart, 2005). Yet because human–AI interaction is still developing as a field, such metaphors have not stabilised. They remain fluid and overlapping, making it difficult to establish consistent conceptual distinctions (Figoli et al., 2025). For instance, framing AI as an “assistant” versus an “agent” suggests different relational models; however, without further unpacking, these distinctions can remain ambiguous. Due to this lack of conceptual clarity, when left unpacked, such metaphors may act as “zombie nouns” (Sword, 2012) or “semantic stopsigns” (van der Maden et al., 2025), encouraging surface-level closure rather than supporting deeper inquiry. This suggests that complementary approaches may help clarify the interactional dynamics to which these metaphors refer.

2.2 Human-AI interaction frameworks

Recent research in HCI and design has produced a range of structured frameworks for analysing co-creative dynamics. These contributions have expanded our understanding of human–AI interaction by approaching it from different angles: some conceptualise co-creation as a mixed-initiative process (Kantosalo & Takala, 2020; Yannakakis et al., 2014), others map recurring interaction patterns or sequences (Grabe, 2022; Rizzi & Bertola, 2025), and others define role configurations within specific design workflows (Liao et al., 2020; Rezwana & Maher, 2023). Despite addressing the same phenomenon, these studies vary significantly in focus and scale, with some offering high-level process models and others detailing functional roles. This variety reflects the layered and multidimensional nature of designer–genAI interaction, as well as the potential of multiple complementary perspectives to enrich our understanding of it.

Despite these differences, certain assumptions recur across the literature, suggesting shared principles that transcend methodological and disciplinary boundaries. Notably, most frameworks share the view that (i) agency is distributed and dynamically negotiated between human and AI actors, and (ii) interaction unfolds through recurring patterns or sequences that can be identified and mapped. These assumptions also underpin the framework introduced in this paper.

While existing models offer robust structures for analysing interaction across larger processes or roles, there remains an opportunity to explore how such dynamics manifest at a finer scale. In particular, little attention has been given to what happens within a single designer–genAI exchange, i.e. the smallest meaningful unit of interaction. In this paper, we refer to this level as the micro-dynamics of the interaction.

2.3 Agency and sense of agency

In human–AI interaction research, agency is a central lens for understanding how humans and computational systems influence one another. Often discussed alongside initiative or process leadership (Gondomar & Mor, 2021; Kantosalo & Takala, 2020; Wu et al., 2021), agency denotes an actor's capacity to act within a given environment (Wilson & Shpall, 2016). The introduction of genAI in the design process has added new layers of automation to design practice (Chesterman, 2019), prompting both designers and researchers to reflect on how agency shifts when working with AI systems (Yun et al., 2019). In this context, scholars increasingly approach agency as distributed. For instance, Rizzi and Bertola (2025), following Wu et al. (2021), differentiate human-led, shared, and AI-led modes; Shi et al. (2023) emphasise relative contribution and mutual influence; and Sun et al. (2020) highlight the need to clarify system boundaries while preserving meaningful human involvement.

Alongside agency, the notion of sense of agency is gaining relevance. Defined as the subjective feeling of initiating and controlling one's actions and their effects (Jeannerod, 2003; Pagliari et al., 2022), this perception, like agency, can be disturbed when interacting with automated systems (Berberian, 2019). Empirical work shows that sense of agency tends to decrease as automation increases (Berberian et al., 2012), supporting earlier findings that users prefer to feel in charge and perceive systems as responsive (Shneiderman & Plaisant, 2004).

In this light, understanding how agency relates to sense of agency is important for creating interactions that are both effective and sustainable (Le Goff et al., 2018; Pagliari et al., 2022). Yet, this specific issue remains underexamined, as existing studies tend to focus on objective performance rather than human experience (Berberian, 2019).

3. Methodology

The literature reviewed above highlights several orientations in current research: metaphor-driven interpretations of genAI, high-level frameworks of co-creative processes, and largely parallel discussions of agency and sense of agency. Within this landscape, the present study takes a complementary position by adopting a practitioner-grounded perspective focused on the micro-dynamics of single designer–genAI exchanges and examining how agency and sense of agency unfold within them.

In this light, this study adopts a Constructivist Grounded Theory (CGT) approach (Charmaz, 2000, 2012), which is well-suited to examining emerging and underdefined domains such as the designer-genAI interaction. Its emphasis on practice-grounded, interpretive analysis (Glaser & Strauss, 1967) aligns with the largely practitioner-led and still-evolving nature of genAI use in design.

Data were collected through fourteen semi-structured interviews with professional designers who had at least one year of regular genAI use in their practice. Following an "across-design" approach (Blackwell et al., 2009), participants were recruited via purposive sampling (Morse & Clark, 2019) from diverse sub-fields—including interaction, industrial/product, service, visual communication, fashion, jewellery, and motion design—to examine shared interaction patterns across domains rather than within a single specialism. They were based in Europe and the United States and reported between one and more than five years of experience with genAI models. Interviews were conducted between December 2023 and June 2024.

During the interviews, participants were asked to reflect in depth on two recent design projects in which they substantially integrated genAI into their workflow. Rather than discussing genAI in general terms, they were prompted to reconstruct concrete interaction episodes, describing how specific inputs were crafted (Lindley & Whitham, 2025), how outputs were evaluated, and how decisions evolved across iterative exchanges. The interviews were coded iteratively through In Vivo, Process, and Initial Coding (Saldaña, 2025). Rather than starting from predefined constructs, codes emerged from participants' descriptions and were grouped into higher-level categories: (i) the roles of the designer, (ii) the roles of genAI, (iii) the actions that constitute the interaction, and (iv) the ways in which interaction is guided. These categories reflect participants' accounts and form the empirical foundation of the framework.

To synthesise these categories, Activity Theory (AT) was introduced as an organising lens (Engeström et al., 1999; Kaptelinin & Nardi, 1997). AT is an analytical model used to understand interactions between elements of an activity mediated by tools within a social context (Kuutti, 1995). Rather than applying AT as a fixed model, its core logic was used as a structural heuristic to interpret the collected data. Specifically, the AT triad of "subject–instrument–object" was used to structure the interaction cycle. In our adaptation (Figure 1), the designer and the genAI are treated as interacting subjects; input and output function as the mediating instruments (e.g., prompts and generated content); and the object is operationalised as the immediate purpose guiding each action (e.g., to consult, interrogate, or instruct).

Figure 1 On the left, the AT triad subject, instrument, and object. On the right, the contextual adaptation of these core elements to the designer–genAI interaction cycle.

Figure 2 The four sub-actions comprising a single designer-genAI interaction cycle.

Building on this, the analysis of participants' accounts indicated that each input–output cycle could be decomposed into four sub-actions: (i) the designer crafts the input, (ii) genAI processes it, (iii) genAI generates the output, and (iv) the designer evaluates it (Figure 2). The distinction between genAI processing and generating is conceptual rather than technical, differentiating the internal transformation of the input from the outward production of an output. A final component was added to capture the extent to which each party influences the generated output: we defined it as the distribution of output contribution. These five elements—subjects, instruments, objects, sub-actions, and contribution—were integrated into a unified conceptual visualisation. This visualisation was refined iteratively and reviewed by five experts in design research and HCI during a visiting period at TU Delft University, whose feedback informed its structure and clarity.

4. Results

4.1 Visualising the designer-genAI interaction cycle

Figure 3 Conceptual visualisation representing a single designer-genAI interaction cycle, decomposed into its core elements (subjects, instruments, sub-actions, objects and contribution).

Figure 3 presents a conceptual visualisation of a single designer–genAI interaction cycle, developed from the coded categories and structured through the four sub-actions informed by AT. The diagram positions the designer and genAI (1) opposite each other, with input and output (2) on the remaining ends of a circular layout, forming a closed loop. Input and output are treated as shared instruments, engaged by both subjects at different moments. Arrows linking subjects and instruments represent the sub-actions (3): solid lines indicate externalisation (e.g., crafting input, generating output), while dashed lines indicate internalisation (e.g., processing input, evaluating output). Arranged clockwise, these sub-actions are: crafting (3A), processing (3B), generating (3C), and evaluating (3D), emphasising the cyclical nature of interaction. Two final arrows mark the concluding two steps: iteration (3F) or disengagement (3E). Transversal arrows (4) represent the object (i.e., purpose) of each sub-action by connecting subjects and instruments, highlighting their mutual relation (e.g., the designer "instructs" the genAI). At the centre of the diagram, two overlapping circles (5) represent the relative contribution of the designer and genAI to the output. Their size ratio visually indicates whether the output is primarily shaped by one actor or is balanced. In this version, the two circles have the same radius, illustrating a balanced contribution.

4.2 The Imagery Modes Framework

After developing the interaction conceptual visualisation, it became possible to explore how this structure reveals different patterns of engagement. The key factor emerging from the data was the level of "output imagery definition"—that is, the clarity of the designer's mental representation of the expected output prior to the interaction, regardless of whether that output is textual, visual, or otherwise. Building on this concept, the designer–genAI interaction cycle (Figure 3) is expanded into the designer-genAI Imagery Modes (IMs) framework (Figure 4). This framework identifies three modes of interaction, each corresponding to a different stage of output imagery definition (Table 1).

Table 1 The three modes of interaction.

Mode of Interaction	Definition	Exemplary Quotes from Participants
Before Imagery	The designer begins with little preconception of the expected output	"I start vague, adding phrases like 'if it seems right to you, feel free to propose something else'"
During Imagery	The designer holds a relatively defined conception of the expected output	"I see it as a conversation. I try to give enough input without restricting its creativity"
After Imagery	The designer has a clear and detailed conception of the expected output	"I give the idea, tell it what to change, and it executes"

Figure 4 The designer-genAI IMs framework: the three interaction modes are positioned along a spectrum ranging from releasing to retaining control.

The imagery modes should not be interpreted as fixed states, but as analytical reference points. In practice, designers are never entirely in a Before Imagery state, since even exploratory situations involve some degree of intention or expectation. Likewise, a complete After Imagery state is rarely achieved, as genAI outputs inevitably diverge, to some extent, from the designer's internal representation.

For this reason, the three modes are best understood as positions along a continuum of control. Here, control refers to the degree of influence the designer exercises over the generated output. Interactions closer to Before Imagery involve greater delegation of control to genAI, as expectations for the output remain loosely defined. Interactions closer to After Imagery involve tighter control, since the desired output is more clearly specified in advance.

Positioned along this continuum, the three modes outline distinct interaction configurations, each integrating five interrellated nuances: (i) how designers craft the input; (ii) how they evaluate the output; (iii) the directional relations (i.e., purpose) between designer and genAI; (iv) the directional relations (i.e., purpose) between input and output; and (v) the distribution of output contribution. Notably, these configurations reflect recurring patterns in the interviews and describe tendencies specific to this study. As such, they should not be understood as fixed or universal, but as open to ongoing adaptation and refinement in future research.

4.2.1 Before Imagery

In Before Imagery interactions, designers craft inputs by embedding broad **criteria**—such as tone, theme, or general direction—without a clear expectation of the final output. These inputs serve to open an exploratory space rather than define specific characteristics, and are often described as quick to formulate and cognitively light. Several participants highlighted how this mode involves deliberately leaving interpretative space to genAI, with one noting: "I didn't decide what goes in each chapter—I let myself be guided by the tool, which made choices that I think were design choices".

Evaluation in this mode centres on **correctness**—assessing whether the output broadly aligns with the initial criteria. However, this can be cognitively demanding, as designers must interpret unfamiliar results against loosely defined expectations. One participant explained: "AI does a lot of very interesting hallucinations, but for me, those hallucinations are harder to explain as my own". Another noted the need for additional verification: "usually a librarian won't tell you things that are wrong, but AI will".

The primary purpose of the interaction, from the designer's perspective, is to **consult** the genAI—to access perspectives, references, or directions beyond their current awareness. GenAI, in turn, **enhances** this process by expanding the available material and introducing unexpected cues that support reinterpretation or the formation of new connections. In this dynamic, the input **triggers** exploration, and the output **expands** it—making the output contribution predominantly **genAI-led**.

4.2.2 During Imagery

In During Imagery interactions, designers embed more developed **ideas** into the input—such as hypotheses, tentative propositions, or narrative and visual intentions—while remaining open to variation. These inputs balance direction and flexibility, conveying a partially formed vision without fixing the output. Participants described this mode as “giving the sketch to genAI to see variations” or constructing prompts that focus on key dimensions, such as “colours, materials, and composition,” to steer exploration without over-constraining it.

Evaluation in this mode centres on **alignment**—whether the output resonates with the designer’s evolving idea. Designers described this as an interpretative judgement. As one participant put it, “it’s about the feel of it… I can tell the moment something disconnects from my story”. Others emphasised maintaining openness while preventing excessive drift: “I give it enough room to think, but I don’t want it to go too wild”. Outputs that introduce meaningful variation can even prompt reframing, as in the words of one of the participants: “sometimes it generates something I didn’t explicitly ask for, but it makes sense… maybe I wanted it but hadn’t found the words yet”.

Within this mode, the designer’s purpose is to **interrogate** the genAI to test, articulate, and refine emerging thinking, while genAI **supports** this process by elaborating, reframing, or extending the idea. Accordingly, the input **anticipates** the output by projecting a conceptual direction, and the output **challenges** the input by introducing alternative perspectives. Contribution in this mode is therefore more **balanced** across the exchange.

4.2.3 After Imagery

In After Imagery interactions, designers embed specific **concepts** into the input—such as form, structure, phrasing, or precise stylistic details—to achieve a highly predictable output. Participants described entering this mode when they already held a clear vision of the desired result and sought to translate it into precise instructions: “the clearer you are, the closer the model gets to doing what you want”, as one put it. Another person noted: “I know what I want, and I’m just trying to find the right words to make it come out”. Crafting such inputs requires effort, as designers articulate their intentions with greater specificity.

Evaluation in this mode centres on **fidelity**—whether the output reproduces the expected concept without adding or omitting elements. Because the designer already holds a clear expectation, this sub-action tends to be more straightforward and less cognitively demanding. The judgment is immediate: the output either matches or deviates from what the designer was expecting, as in the words of one interviewee, “if elements are added or missing…it’s clearly a mismatch with what I intended”. When deviations occurred, they were experienced as errors to be corrected rather than prompts for reinterpretation.

Within this mode, the designer’s purpose is to **instruct** the genAI, conveying a request intended to be executed with minimal variation. GenAI’s role, in turn, is to **substitute** for the designer in performing the execution. Accordingly, the input **describes** the desired output in detail, and the output **mirrors** this specification as closely as possible, making the contribution primarily **designer-led**.

All the nuances characterising the three modes are presented in Figure 5.

Figure 5 Overview of the three interaction modes and their defining nuances.

4.2.4 Agency and sense of agency across the three modes

Finally, the data analysis reveals that the three modes also shape how both agency and sense of agency unfold within the interaction.

In Before Imagery interactions, designers provide broad criteria and leave interpretative space to the genAI. Agency is low, as the system leads the generative direction. Despite this, sense of agency can remain high, since designers consciously delegate control and evaluate the output against loosely defined expectations. As one participant described, they asked the model to “show me where you can take me”, treating the results as material to “play with, tweak… and go back and forth”. Conversely, when the output lacked novelty or relevance, the sense of agency declined. As another participant noted, “the generated images looked very generic, like very bad fantasy art.”

In During Imagery interactions, designers engage genAI with a partially formed idea to explore variations within a defined space. Agency is more balanced: the designer sets boundaries, and genAI contributes within them. Sense of agency hinges on whether the output helps advance the idea. When it does, designers report they "usually manage to get what I want", "feeling 80%… maybe even 90% at the helm". By contrast, when results are "literal… stereotyped" and lack a "human touch", they experience a "disconnection from the story", often reverting to more familiar or controllable methods.

In After Imagery interactions, designers instruct genAI using clearly defined concepts, setting strict expectations. Agency is high, as the designer dictates the output generation. However, the sense of agency can be fragile: strict expectations mean that even small deviations may feel like a loss of control. One participant described using a layered prompting strategy where "every colour that is written appears, every material that is written appears, and every shape that is written appears, and nothing else is added or removed". When genAI responded faithfully, they described it as "a brush to my instruction". By contrast, another participant, working on 3D image generation, reported that the genAI often produced "random things", sometimes even "not figurative images". Expanding on this, they noted that these outputs are difficult to edit once generated, making it hard to adjust them as desired: "it's not like working on an open file—I can't go in and change things, so in the end it doesn't feel like I made any of the decisions".

5. Discussion

5.1 A fluid, non-linear interaction

The IMs framework analyses the designer–genAI interaction at a finer scale by decomposing a single input–output cycle into its constituent actions and positioning it within one of three imagery modes. By structuring interaction at the level of individual cycles, the framework enables a situated description of the micro-dynamics unfolding within each exchange. In this way, it offers a complementary analytical lens that is decoupled from specific design phases (e.g., ideation, refinement) or fixed goals (e.g., creativity support). Instead, it provides a structure that can be situated across diverse contexts and tasks, allowing designer–genAI dynamics to be examined consistently.

For example, one participant described beginning an interaction as follows: "Normally I start with something quite vague. I use the genAI with text making to give me like a very first prompt". Within the IMs framework, this corresponds to Before Imagery: the designer does not yet hold a clear mental representation of the expected output and relies on genAI to explore possible directions. Identifying this cycle as Before Imagery clarifies key aspects of the interaction—such as how the input is crafted and how the output is evaluated—consistent with the patterns described in the Results section.

Beyond analysing individual exchanges, the framework also enables the tracing of interaction sequences by reassembling multiple cycles. For instance, the same participant continued describing their interaction sequence: "So, I will explain my idea, what I had in mind […] I will tell it to give me something very short, like a good keyword", mirroring a During Imagery interaction. Later, they added, "And then I start from there for the image making", reflecting an After Imagery interaction. Together, these steps reveal a progression from Before Imagery to During Imagery and finally to After Imagery (Figure 6). This progression also reflects shifts in output contribution—from genAI-led, to more balanced, and eventually to designer-led—tracing a trajectory from releasing control to retaining it. By classifying each cycle according to its imagery mode, the framework makes these otherwise implicit shifts visible.

Figure 6 The interaction sequence followed by one participant.

Importantly, the data show that such sequences are not necessarily linear. Designers do not always move from Before to During to After Imagery in a fixed order. For instance, a designer may begin with a precise request (After Imagery), step back to explore broader stylistic variations (During Imagery), then attempt another targeted generation aligned with the updated concept (After Imagery), and finally reopen the problem space entirely (Before Imagery). In this sense, designers may fluidly shift between imagery modes rapidly and recursively. Treating interaction sequences as a unified process would obscure these internal transitions, making it difficult to understand how and why a particular output was achieved. In this context, while metaphorical interpretations of genAI, such as "assistant" or "executor", can be useful, they may not always capture the shifting dynamics that occur from one interaction cycle to another.

Given the fluid and non-linear nature of the designer-genAI interaction, the IMs framework provides a structured method for comparing and interpreting interaction sequences, helping to address a broader challenge in genAI research: the difficulty of documenting when, how, and why AI is integrated into design processes (Arnold et al., 2024; Dalsgaard et al., 2016). Greater traceability can support more informed discussions of authorship, accountability, and design rationale (Shukla et al., 2025). By surfacing the micro-dynamics of the interaction, the framework supports more rigorous documentation and analysis. It can complement reflective and systemic models, helping researchers develop clearer insights into oversight, traceability, and value alignment (Cavalcante Siebert et al., 2023).

5.2 Bridging agency and sense of agency

Beyond tracing interaction sequences, the IMs framework offers a way to address the theoretical gap between agency and sense of agency by clarifying how they vary across the three modes of output imagery.

Starting from agency, a linear pattern emerges mirroring the release-retain control spectrum: as interactions move from Before to During to After Imagery, the designer's capacity to influence the output increases. In Before Imagery interactions, they relinquish control and allow genAI to take the generative initiative. In After Imagery interactions, by contrast, they hold the lead through more detailed and directive inputs.

However, sense of agency does not seem to follow the same linear progression. Participant accounts show that high actual agency does not always lead to high perceived agency, and vice versa. As Pagliari (2022) argues, sense of agency depends less on how much control one objectively has and more on whether the outcome aligns with prior expectations. As the results show, when predictions and outputs align, even in Before Imagery, where genAI leads, sense of agency can remain positive. Conversely, when outputs deviate from tightly specified expectations, as in After Imagery led by the designer, sense of agency can drop markedly. In other words, while agency varies linearly across modes, sense of agency hinges on the coherence between expectation and outputs within each interaction mode (Figure 7).

Building on this, the framework enables comparisons with broader interaction paradigms. Before Imagery resembles search-engine logic (e.g., Google Search): the designer has limited direct control over how results are presented from their query, but may still feel in control when the outputs match their exploratory intent. After Imagery aligns more closely with traditional CAD software: the designer exercises high control, and the sense of agency is sustained when execution accurately follows instructions. From this perspective, the closer interactions move toward the poles of the control spectrum, the more familiar the interaction pattern becomes, since they resemble established paradigms such as exploratory querying or directive execution, where expectations about control and system behaviour are clearer. During Imagery, however, it does not fit neatly into either pattern. In this mode, control and expectations are negotiated step by step rather than clearly defined in advance. For this reason, it does not follow the more predictable and deterministic patterns of the Before and After Imagery modes. This makes it a distinctive configuration of designer–genAI interaction, possibly explaining why it may be more difficult to manage, describe, and teach.

Figure 7 The relation of agency and sense of agency in the IMs framework.

5.3 Applying the IMs Framework

Finally, several potential uses of the IMs framework can be outlined. These should not be read as prescriptive guidelines for professional practice—where work is shaped not only by design decisions but also by organisational dynamics, deadlines, and external constraints—but as analytical and reflective resources. In this sense, the framework may inform scholarly research, design education, and the development of future genAI-infused design tools.

First, as discussed earlier, the framework can serve as a lens for analysing both individual interaction cycles and longer sequences with greater detail. For example, during early ideation, a sequence of input–output exchanges can be examined to distinguish which outcomes were clearly anticipated by the designer and which emerged through genAI-driven variation. This distinction can support a more critical use of genAI, allow clearer assessments of human contribution within a project, and strengthen reflections on authorship and responsibility.

Second, given the interplay between agency and sense of agency, the framework can help designers anticipate the kind of interaction they are entering and align their expectations accordingly. For example, when engaging genAI to explore stylistic alternatives, recognising the interaction as closer to Before Imagery signals that broader variation and unexpected outputs are likely. Conversely, operating closer to After Imagery suggests a more controlled and predictable result. By making this distinction explicit, designers can better align their expectations with genAI's behaviour, reducing frustration and enabling more deliberate adjustments when outcomes diverge from what was anticipated.

Third, the three imagery modes can also be adopted deliberately as a model of use. A designer working under tight constraints may choose to operate primarily in After Imagery mode in order to retain stronger control over each generated output. In practice, this could involve configuring a text-to-text model with precise instructions that restrict variation and emphasise execution. Conversely, during early exploration, a designer may instruct genAI to provide only broad variations or alternative directions, without committing to a specific form, thereby keeping the interaction open and exploratory. Designers may also decide in advance to limit the number of interaction cycles—for example, stopping after a predefined number of iterations—to prevent over-iteration and maintain decision momentum.

6. Conclusions

This paper analyses the micro-dynamics of designer–genAI interaction within a single input–output exchange. In doing so, it complements metaphor-driven interpretations by unpacking what occurs within each interaction cycle, adds a finer-grained perspective to co-creative frameworks, and brings agency and sense of agency into closer relation within concrete interaction units.

Using CGT and AT, a single interaction cycle was decomposed into a conceptual visualisation and articulated into the IMs framework, comprising Before, During, and After Imagery. The findings highlight the fluid and non-linear character of designer–genAI interaction: designers shift between modes rapidly and not necessarily in a fixed sequence. Agency varies linearly along the release–retain control spectrum, while sense of agency depends on alignment between expectations and outputs within each mode. During Imagery emerges as a distinctive configuration of the designer-genAI interaction, characterised by iterative negotiation between designers and genAI. The framework may also inform practical applications by supporting clearer documentation of interaction sequences, more explicit expectation-setting, and more deliberate engagement with genAI.

The study presents intermediate-level knowledge (Höök & Löwgren, 2012) grounded in qualitative data from a specific group of practitioners and tools. As such, the findings may not fully reflect the diversity of practices across domains, tools, or levels of expertise. Future research may refine and test the framework in broader contexts, using varied methodological approaches, and explore how it can inform educational or professional practices that support the critical and intentional integration of genAI into design workflows.

7. References

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