

Interaction-Augmented Instruction: Modeling the Synergy of Prompts and Interactions in Human-GenAI Collaboration

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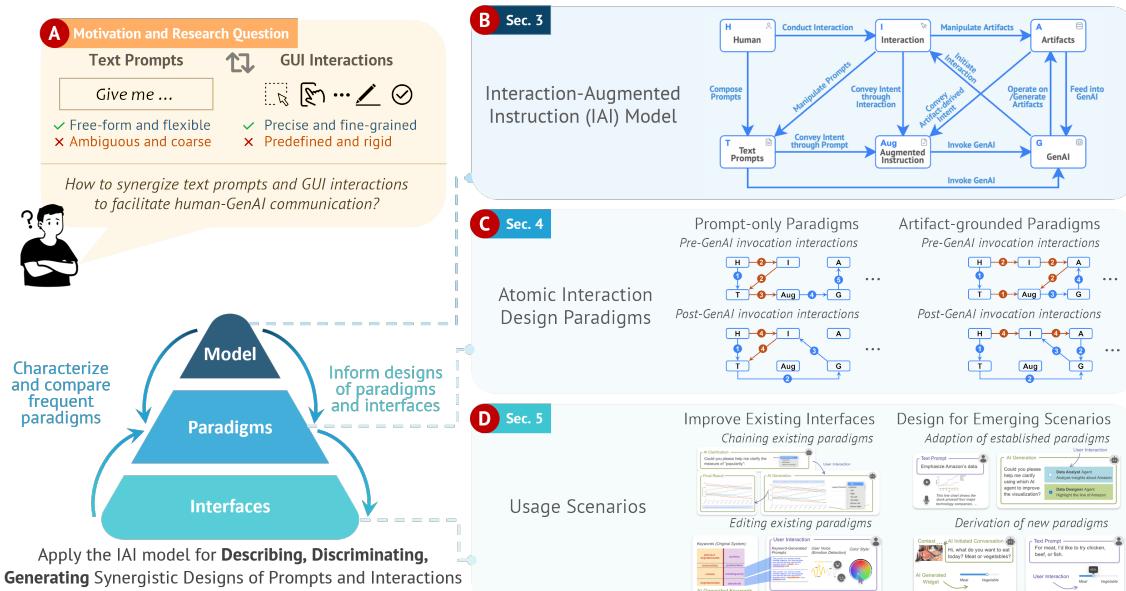


Fig. 1. This paper addresses the research question of (A) how to synergize text prompts and GUI interactions to facilitate human–GenAI communication. We propose the Interaction-Augmented Instruction (IAI) model (B). The model enables systematic characterization and comparison of existing paradigms (C) and guides the design of new interfaces (D), demonstrating its *descriptive, discriminative, and generative power* for shaping future GenAI systems.

Text prompt is the most common way for human-generative AI (GenAI) communication. Though convenient, it is challenging to convey fine-grained and referential intent. One promising solution is to combine text prompts with precise GUI interactions, like brushing and clicking. However, there lacks a formal model to capture synergistic designs between prompts and interactions, hindering

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their comparison and innovation. To fill this gap, via an iterative and deductive process, we develop the Interaction-Augmented Instruction (IAI) model, a compact entity-relation graph formalizing how the combination of interactions and text prompts enhances human-GenAI communication. With the model, we distill twelve recurring and composable atomic interaction paradigms from prior tools, verifying our model's capability to facilitate systematic design characterization and comparison. Four usage scenarios further demonstrate the model's utility in applying, refining, and extending these paradigms. These results illustrate the IAI model's descriptive, discriminative, and generative power for shaping future GenAI systems.

CCS Concepts: • Human-centered computing → Interaction paradigms.

Additional Key Words and Phrases: Generative AI, Text Prompt, Interaction, Human-GenAI Collaboration

ACM Reference Format:

Leixian Shen, Yifang Wang, Huamin Qu, Xing Xie, and Haotian Li. 2025. Interaction-Augmented Instruction: Modeling the Synergy of Prompts and Interactions in Human-GenAI Collaboration. In *Woodstock '18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY*. ACM, New York, NY, USA, 26 pages. <https://doi.org/10.1145/nnnnnnnn.nnnnnnnn>

1 Introduction

Generative AI (GenAI) has rapidly become a general-purpose technology, enabling new intelligent applications across domains such as design [65], education [37], and data analysis [31]. Modern large language and multimodal models can interpret open-ended text prompts and generate diverse outputs (e.g., text, image, and data analysis dashboards), making the text prompt interface the dominant paradigm for human-AI communication [67]. By allowing users to express complex intents in natural language, text prompts offer great flexibility, allowing users “ask anything” and receive tailored responses.

Despite the convenience, free-form text prompts are often insufficient to convey fine-grained and nuanced human intent when precise instructions are required. This is due to the ambiguity and the coarse nature of natural language [60, 66, 72]. For instance, in image editing, a user might want to modify “*the upper-right flower petal*”, but a text prompt alone is hard to accurately localize that target visual element. Likewise, in coding, asking “*write a loop to process this data*” could imply different iteration strategies. Correspondingly, in practice, users often struggle to articulate sufficient detail or to break down complex goals into a single prompt, resulting in suboptimal or hard-to-control AI behavior.

To address these limitations, a promising strategy is to combine general-purpose but imprecise text prompts with dedicated interactions (e.g., clicks, drags, brushes, etc.) through graphical user interfaces (GUIs), as shown in Fig. 1-A. The synergy enables both flexible and fine-grained control by users. For example, OpenAI Canvas [57] and Cursor [5] let users select a specific text segment or code block and then issue a focused prompt that applies only to that context. Tableau AI [75] uses LLMs to suggest context-aware follow-up questions on GUI for user selection during data exploration. Research prototypes following this strategy have also emerged, exploiting the strengths of both natural language and direct-manipulation input for diverse tasks, such as coding [22], writing [36], data visualization [85], and image editing [47]. Despite the wide and diverse applications, the strategy has not been formalized as a comprehensive *interaction model* to guide related research and practices. As a pioneering study in the HCI field points out [9], these “point-like” research demonstrations of the strategy are often insufficient due to the challenges of transforming task-specific demonstrations to broader real-world applications and understanding the advancement of related techniques. It is essential to propose general interaction models to facilitate the careful examination of existing designs (*descriptive power*), the comparison between design variations (*discriminative power*)¹, and the consequent innovation of new interaction designs for emerging tasks (*generative power*) [8, 9, 42].

¹Manuscript submitted to ACM

Towards this goal, there has been a series of previous research that attempted to reveal and advance the interaction-text prompt synergy. Gao *et al.* [25] and Hu *et al.* [30] have developed taxonomies of interaction paradigms for interactive GenAI applications, such as GenAI as a medium, tool, partner, and mediator. However, the taxonomy is mostly descriptive and is difficult to use to guide the generation of new designs for new scenarios. Riche *et al.* [60] proposed AI-Instruments, extending instrumental interaction [8] by treating prompts themselves as manipulable interface objects, guided by three principles: Reification, Reflection, and Grounding. These principles enrich the considerations for generating new interaction designs but fall short in comparing multiple designs within a model that explicitly represents the interplay between text prompts and other interaction modalities.

To fill this gap, through a deductive and iterative process, we propose the Interaction-Augmented Instruction (IAI) model: a compact entity-relation graph that makes explicit how precise GUI interactions and free-form prompts are composed into the executable instructions consumed by GenAI (Fig. 1-B). The model comprises six entities: Human (**H**), Interaction (**I**), Text Prompt (**T**), Augmented Instruction (**Aug**), GenAI (**G**), and Artifact (**A**). By consolidating candidate roles into this minimal set, the model highlights **Aug** as the single explicit input to GenAI, thereby simplifying comparison across paradigms and clarifying how different interfaces combine **T**, **I**, and **A** to construct **Aug**. We further systematically enumerated all pairwise relations and preserved only those that are semantically meaningful, discriminative, and interpretable (Table 1).

Building on this foundation, to examine if our IAI model can be generally applied to describe and differentiate existing GenAI systems' interfaces, we revisit a curated corpus of GenAI-powered interactive systems and map each system's interaction workflow to one or more directed paradigm graphs (Fig. 1-C). From the corpus, we distill twelve frequent and composable atomic paradigms organized by interaction timing (pre- or post- GenAI invocation) and resource availability (prompt-only vs. artifact-grounded). These paradigm graphs based on the IAI model serve as high-level abstractions of interaction workflows, enabling tools to be clustered and compared.

The IAI model provides not only a theoretical lens but also a practical framework for future interface design. The twelve design paradigms derived from the IAI model can be applied, refined, and extended for creating new interfaces that meet diverse scenario demands. Unexplored interaction design paradigms are also revealed from comparing the existing paradigms with the entire IAI model. To demonstrate the power of generating new interface design and novel interaction paradigms, we present four usage scenarios that bridge conceptual models with actionable design processes (Fig. 1-D). These usage scenarios show how the IAI model can guide the iterative enhancement of existing tools by chaining or editing existing design paradigms, while also supporting the adaptation of established paradigms and the derivation of new atomic paradigms for emerging scenarios. Looking forward, we envision the IAI model as a foundation for advancing human–GenAI communication, opening new opportunities to design more transparent, controllable, and creative GenAI systems. To summarize, our work makes three main contributions:

- Interaction-Augmented Instruction model (Sec.3): We propose a new interaction model formalizing how task-specific interactions and free-form prompts jointly generate instructions for GenAI, enabling richer human–AI collaboration.
- Design paradigms (Sec.4): We apply this model to existing interfaces by encoding each as directed paradigm graphs, deriving 12 recurring and composable atomic paradigms, enabling systematic design characterization and comparison.
- Usage scenarios (Sec.5): We use four usage scenarios to demonstrate how our model can improve existing interface design and generate new design paradigms for emerging scenarios.

2 Related Work

Prior work on human–GenAI collaboration covers communication paradigms, design patterns, and theoretical models; we review these to highlight progress and motivate a unified model of interaction-augmented instructions.

2.1 Human–GenAI Communication

Human–GenAI communication spans a spectrum of interface strategies, from free-form text prompting to fully encapsulated tools and hybrid paradigms that combine prompting with GUI interactions.

Free-form text prompts remain the dominant way for human–GenAI communication due to their flexible, expressive, and low-friction [21, 84]. However, prompt-only interaction has well-documented limitations: natural language is often ambiguous, underspecified, or ill-structured for task-specific operations, which increases iteration cost and reduces control [60, 66, 72]. Empirical studies highlight recurring challenges such as prompt formulation, disambiguation, and intent steering—for example, users struggle to localize visual elements precisely through language alone [23, 52] or to specify the exact semantic behavior desired in code edits [22, 88].

Another line of interface design has been to encapsulate GenAI capabilities within backend agents or domain-specific tools [7]. In such designs, the system exposes a constrained interface (*e.g.*, widgets, templates, or menus) [44, 51, 80] or totally automate the process while GenAI executes domain logic behind the scenes. For example, Textoshop [51] allows text editing entirely through drawing software-like interactions, with prompts handled internally; fully automated agents similarly hide prompting from the user [64, 91]. This lowers user burden but constrains openness and the expressive flexibility of prompting.

A more flexible and increasingly prevalent approach is to combine prompting with GUI interactions—what we call interaction-augmented instructions. Here, prompts are enriched by targeted user actions such as clicking, brushing, sketching, or selecting [25, 30, 66]. These interactions may occur before the GenAI invocation, *e.g.*, selecting elements to constrain the scope of a prompt [19, 23, 46, 47, 52, 79, 86], organizing multiple prompts into structured forms such as trees or graphs [22, 27, 84, 88], sketching to guide content generation [35, 43, 56, 92], annotating text to extend context or highlight specific information [63], or after it, *e.g.*, clarifying user intent through follow-up queries [3, 6, 13, 27, 49], presenting suggestions for human confirmation [4, 36, 83], converting prompt into structured GUI components [14, 89], or enabling direct post-generation artifact manipulation [26, 32, 58, 73, 77, 85]. Together, these paradigms illustrate diverse strategies for balancing the openness of prompting with the precision of interaction.

While many studies demonstrate the effectiveness of such hybrid paradigms in task-specific contexts, prior work often remains fragmented that do not generalize easily to broader real-world applications [9]. To advance the field, it is essential to propose general interaction models that can systematically capture these designs, enable structured comparison across paradigms, and inspire new interaction designs. Our work addresses this need by introducing a unifying formalism for describing, discriminating, and generating interaction-augmented instruction paradigms.

2.2 Human–GenAI Interaction Models and Design Patterns

Interaction design in modern UIs has evolved from early WIMP and direct-manipulation paradigms to richer post-WIMP models that foreground instruments and objects over low-level commands [38, 78]. Direct-manipulation interfaces emphasized immediate, visible control—users act on representations of domain objects and observe one-to-one effects [68]. Building on this view, Beaudouin-Lafon’s Instrumental Interaction framed instruments as mediators between user actions and artifacts, where each instrumented action maps directly to a target operation [8, 11]. Subsequent work

introduced “substrates” as “places for interaction”, a mechanism to combine power and simplicity by structuring where and how instruments apply in complex interfaces [50].

These classical models are well suited to deterministic manipulation, but they assume a one-to-one relation between an interaction and its effect on an artifact. Generative systems violate that assumption: a single high-level instruction (e.g., a free-form text prompt) can trigger multiple, nonlocal transformations across an artifact or even across multiple artifacts. This multiplicity and indirection require rethinking how instruments, intentions, and objects are modeled in an era of GenAI.

Recent HCI work has begun to explore this space. A series of surveys and taxonomies catalog interaction modalities and recurring patterns. For example, Lehmann *et al.* [40] analyze how UI affordances mediate access to model capabilities, Luera *et al.* [48] review input modalities across GenAI applications, Gao *et al.* [25] propose a taxonomy of human–LLM communication modes, and Hu *et al.* [30] identify general paradigms, *i.e.*, GenAI as medium, tool, partner, and mediator. Shen *et al.* [66] focus specifically on interaction-augmented instructions, outlining four core purposes for interaction, *i.e.*, restricting, expanding, organizing, and refining prompts. Complementing these descriptive efforts, Riche *et al.* [60] introduce AI-Instruments, extending instrumental interaction [8] to generative settings by making prompts themselves manipulable objects and articulating principles of reification, reflection, and grounding.

Prior work has laid important groundwork but remains limited in different ways. Taxonomies of GenAI interaction paradigms [25, 30] primarily offer descriptive power, enumerating recurring patterns without providing a mechanism to compare or compose them. In contrast, AI-Instruments [60], grounded in instrumental interaction [8], articulate generative principles for reifying and reflecting user intent, but they stop short of offering descriptive and discriminative power across diverse system interfaces. This paper is intended to fill that gap by providing a formal model for describing, discriminating, and generating interaction-augmented GenAI paradigms.

3 Interaction-Augmented Instruction Model

To systematically capture the synergy between text prompts and interactions in GenAI system interfaces, we propose the *Interaction-Augmented Instruction Model*, which is a formal, entity–relation graph that unifies general GUI interaction concepts with new constructs introduced by GenAI (Fig. 2). It distills the essential components of human–GenAI communication and their relations, enabling descriptive, discriminative, and generative analysis of diverse interfaces. This section first describes how we derive the key model concepts, *i.e.*, entities (Sec. 3.1) and relations (Sec. 3.2), and then discusses applying these concepts to represent an interface design with directed graphs (Sec. 3.3).

3.1 Entities

The IAI Model comprises six core entities: **Human (H)**, **Interaction (I)**, **Artifact (A)**, **Text Prompt (T)**, **Augmented Instruction (Aug)**, and **Generative AI (G)**. Concretely, we treat an entity as a semantically coherent object or agent in the interaction ecology. Table 1 provides an overview for all entities and relations between them.

We derived the entities through an iterative, deductive process that begins with asking a simple question: what are the irreducible elements that appear in the common prompt-driven and interaction-driven paths in practice? Two empirically ubiquitous paths served as the starting point. The first is the canonical *prompt-driven flow*, $H \rightarrow T \rightarrow G \rightarrow A$, in which a **human (H)** composes a **text prompt (T)** that the **GenAI (G)** model executes to produce or modify an **artifact (A)** [39, 60]. The second is the general *GUI interaction flow*, $H \rightarrow I \rightarrow A$, in which a **human (H)** leverages **interactions (I)** on GUIs to act on an **artifact (A)** [8, 68]. Based on the two interaction paths, three distinctions are critical to derive our model.

First, to capture the qualitative differences between modalities, we separate **Text Prompt (T)** from **Interaction (I)**. Conceptually, **T** is a free-form, general-purpose, natural language specification of intent (e.g., “*make the flower red*”). **I** denotes focused, modality-specific operations (e.g., click, brush, drag, sketch, widget selection) that supply concrete referents or constraints (e.g., a brush mask, a bounding box, a selected code block). This separation matters because **T** and **I** differ sharply in expressivity, precision, and in how the model understands them. However, such separation is not sufficient to represent what the model actually consumes in many practical GenAI workflows.

To address the issue, secondly, we introduce **Augmented Instruction (Aug)** as a new entity. In GenAI system interfaces, text prompts and interactions are not independent “inputs” that the model somehow interprets in isolation. Interactions often produce structured, non-linguistic constraints (e.g., pixel masks, coordinate ranges, AST node identifiers, selected table rows or text segments, slider parameters) that must be encoded, normalized, and attached to a prompt in a machine-readable form [1, 21, 45, 47, 63]. Viewing **Aug** as the single, explicit input to GenAI simplifies paradigm comparisons, as tools differ mainly in how they combine **T**, **I**, and **A** to build **Aug**.

Third, during iteration we consolidated several auxiliary entities (found in Sec.2.2) into the six core entities to keep the model parsimonious while maintaining expressiveness. Concretely: (1) **Context inputs** (e.g., retrieved passages, prior conversation state, uploaded reference files) are modeled as part of Artifact (**A**) because they function as domain objects that ground instructions [25]. Their inclusion is modeled via $A \rightarrow \text{Aug}$ (artifact-derived constraints) or $A \rightarrow G$ (artifact supplied as raw model context). (2) **Temporary interaction products** (e.g., highlighted spans, sketched regions, intermediate masks, or annotation buffers) are treated as manifestations of Interaction (**I**) rather than independent entities [30]. They have only transient semantic life: they exist to constrain or point to artifacts or prompts and then are encoded into instructions or discarded. (3) **Widgets** have two aspects: when a widget is a UI primitive invoked by the human it is part of Interaction ($H \rightarrow I$) [22, 52], and when it is generated by the model it is represented as an $AI \rightarrow$ interaction proposal ($G \rightarrow I$) that the human may accept ($I \rightarrow T$ [3], $I \rightarrow \text{Aug}$ [81], or $I \rightarrow A$ [77]). This treatment preserves provenance without inflating the entity set. (4) **External tool** invocation is treated as part of GenAI’s internal behavior ($G \rightarrow A$). Many systems route domain-specific executors (e.g., image editors, compilers, specialized APIs) behind the model; these are execution mechanisms rather than affecting interaction paradigm design [66]. Modeling them as separate entities would conflate execution architecture with the interaction paradigms we aim to capture.

Putting these together yields six entities (Table 1), and each plays a distinct semantic role. Conceptually the six-entity set is *necessary*: removing any entity collapses an entire class of workflows, e.g., without **I**, interaction-augmented cases degenerate to prompt-only; without **T**, prompt-only systems vanish; without **Aug**, interaction-infused instructions cannot be distinguished from raw prompts; without **A**, there is no target object; without **G** or **H**, agency is undefined. They are also *sufficient* to express human–GenAI communication paradigms with the interplay of interactions and prompts, as they are a universe of all nodes in both prompt-driven interaction flow and GUI interaction flow. This point is further justified through revisiting existing research tools in Sec.4.

3.2 Relations

Relations denote the directed channels through which information, constraints, or control flow between entities. Our modeling goal is to retain only the necessary linkages, ensuring that relations remain semantically meaningful, discriminative, and easy to interpret in a given design. To this end, we adopt three guiding principles. (1) *Semantic meaningfulness*: a relation must denote a substantive and interpretable flow of information or control [30, 59]. For example, representing $T \rightarrow A$ (a prompt directly manipulating an artifact) is inappropriate, as it obscures the generative process; such flows should instead be realized as $T \rightarrow G \rightarrow A$ or $T \rightarrow \text{Aug} \rightarrow G \rightarrow A$. (2) *Discriminative value*: a relation

should contribute to distinguishing paradigms rather than restating ubiquitous background actions [9, 42]. For instance, $H \rightarrow A$ (upload or inspection) is common across nearly all systems and adds little explanatory value, so it is treated as background provisioning rather than a defining relation. (3) *Agency and provenance preservation*: a relation must preserve clarity over who initiates and owns an instruction [2, 55]. Thus, flows such as $G \rightarrow T$ or $G \rightarrow Aug$ are excluded:

Table 1. Entities and Relations in the Interaction-Augmented Instruction Model.

Entity	Description and Constraints	Linked Entities (Relation)
Human (H)	The end user who expresses intent and interacts with the GenAI system interface via text prompts and GUI actions. Cannot manipulate the AI directly except through these inputs.	<p>H → T: The user writes and refines a text prompt, which is the primary natural-language instruction conveying intent.</p> <p>H → I: The user performs interactive actions (e.g., clicking, highlighting, dragging) on the interface or artifacts to supplement or refine the prompt.</p>
Text Prompts (T)	Natural-language instructions written by the user to convey intent. Intuitive but may be ambiguous or incomplete. Used alone or as part of a richer instruction for GenAI	<p>T → Aug: The text prompt is incorporated into the augmented instruction (combined with interaction-derived information).</p> <p>T → G: The text prompt alone is sent to the GenAI as input for generating or operating on artifacts.</p>
Interaction (I)	Supplemental user actions (e.g., clicking, selecting, annotating) that add constraints or context to prompts. They refine the AI's understanding but do not generate output independently.	<p>I → Aug: Interaction inputs are integrated into the augmented instruction, adding detail or constraints to the original prompt.</p> <p>I → T: An interaction may modify the text prompt itself.</p> <p>I → A: The user's interactions act directly on domain artifacts (e.g., clicking/highlighting parts of an image or document) to specify or restrict the scope of the GenAI task.</p>
Augmented Instruction (Aug)	The combined instruction delivered to GenAI, formed by merging the text prompt with information derived from interactions. It encodes the complete intent for the AI and only exists as an input to the GenAI system.	Aug → G: The augmented instruction is passed to the GenAI for execution. GenAI uses this enriched instruction to generate content or perform actions.
Artifacts (A)	Domain objects (e.g., text, image, code) that GenAI operates on. They are the targets of user interactions and AI outputs, but not instructions themselves.	<p>A → Aug: User interactions on an artifact (e.g., highlighting a paragraph) are incorporated into augmented instruction.</p> <p>A → G: Artifacts or extracted features used as contextual input to GenAI.</p>
Generative AI (G)	The model (e.g., LLM or diffusion model) that interprets the augmented instruction and generates or edits artifacts. It acts only upon receiving input.	<p>G → A: Upon receiving the augmented instruction, GenAI operates on artifacts by generating new content or triggering operations on domain objects (e.g., creating an image, editing a document).</p> <p>G → I: Can initiate interactions (e.g., suggesting follow-up options or UI elements for user action).</p>

while the model may propose candidate prompts or widgets (captured as $G \rightarrow I$), they only become active instructions after explicit user or UI mediation ($I \rightarrow T$ or $I \rightarrow Aug$), ensuring agency and traceability are maintained.

Taken together, these principles justify modeling only a small, purposeful subset of all possible relations rather than the full combinatorial space. For each entity pair (X, Y), we evaluate whether X can produce information or control that Y can meaningfully consume in the context of human–GenAI communication. If so, the relation is included with its semantics recorded; if not, it is excluded with an explicit rationale. Table 1 presents the resulting relation set. Detailed explanations are as follows:

- **Human (H).** Humans possess intent and decision authority but do not execute generation themselves. Consequently, humans can compose and revise textual instructions ($H \rightarrow T$) and perform focused interactions ($H \rightarrow I$) such as highlighting, brushing, or selecting. Humans also provide or inspect artifacts through interfaces. However, since the action of upload or inspection is ubiquitous across systems and does not by itself distinguish paradigms, we treat $H \rightarrow A$ as background behavior rather than a central comparative relation (no $H \rightarrow A$). Critically, humans do not directly perform generation (no $H \rightarrow G$) without going through instructions.
- **Text Prompt (T).** T is a general-purpose, free-form specification of intent. It can be sent directly to GenAI ($T \rightarrow G$) or be combined with interaction-derived information to form an augmented instruction ($T \rightarrow Aug$). T does not act on artifacts directly (no $T \rightarrow A$).
- **Interaction (I).** Interactions are focused, often single-purpose operations. Interactions can operate on artifacts ($I \rightarrow A$) like selecting target elements, modifying or augmenting prompts ($I \rightarrow T$), or feeding information into the augmented instruction ($I \rightarrow Aug$). Interactions cannot evoke GenAI to generate by themselves (no $I \rightarrow G$): they are not generators but mediators of specificity.
- **Augmented Instruction (Aug).** Augmented instruction represents the instructions beyond pure NL prompts that the GenAI will execute. By definition, Aug is constructed from prompt and interaction inputs ($T \rightarrow Aug, I \rightarrow Aug$) and can additionally incorporate direct artifact-derived context ($A \rightarrow Aug$) when a selection or context snippet is encoded into the instruction. The only valid execution path from Aug is into the model ($Aug \rightarrow G$); Aug does not itself perform artifact edits (no $Aug \rightarrow A$). Treating **Aug** as the single, explicit input to GenAI makes paradigm comparisons straightforward: different tools differ chiefly in how they build **Aug** (which combinations of **T**, **I**, and **A** feed into it). Please refer to Sec.4.2 for more details.
- **Artifact (A).** Artifacts are the domain objects—texts, images, code, datasets—that provide both targets and context. Artifacts are passive in the relation set: they do not autonomously produce text prompts (no $A \rightarrow T$) or initiate interactions (no $A \rightarrow I$). Relevant relations include $I \rightarrow A$ (interactions operate on artifacts to select or annotate), $A \rightarrow Aug$ (artifact content or references can be incorporated into the augmented instruction), and $A \rightarrow G$ (artifacts can be provided directly as model input). The distinction between $A \rightarrow Aug$ and $A \rightarrow G$ is meaningful for paradigm design: $A \rightarrow Aug$ indicates artifact-derived constraints become part of the composite instruction, whereas $A \rightarrow G$ indicates the artifact (as well as its extracted features) is supplied as raw model context.
- **Generative AI (G).** GenAI is the executor, it accepts an instruction ($T \rightarrow G$ or $Aug \rightarrow G$) and produces or modifies artifacts ($G \rightarrow A$). In mixed-initiative paradigms, GenAI may also present interaction affordances or clarification options ($G \rightarrow I$) to solicit further user input. GenAI cannot directly produce **Aug** (no $G \rightarrow Aug$), as it must embed user interaction-derived information; likewise, when GenAI generates prompt suggestions, users need to take explicit interaction to turn it into **T** (*i.e.*, no $G \rightarrow T$). We define this constraint following the well-known human-AI interaction

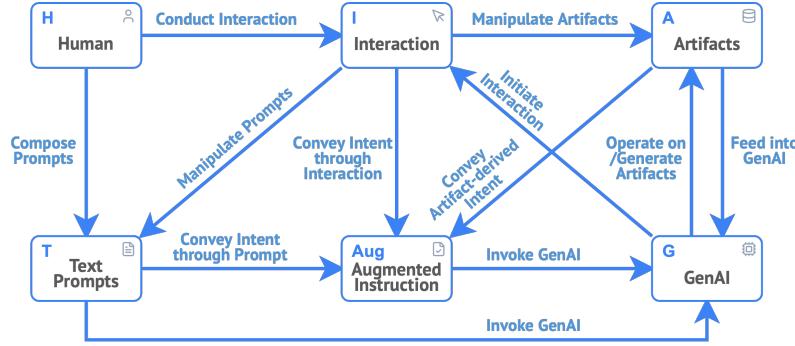


Fig. 2. Interaction-Augmented Instruction Model.

guidelines, where users should be aware of AI actions and have full control over AI [2]. Without the constraint, AI can prompt itself without human control, violating the principles.

The relation set is *necessary* because each retained relation reflects a non-reducible semantic flow, consistent with the principle of semantic meaningfulness. It is also *sufficient* because, after systematically enumerating and pruning all possible pairs, the remaining compositions span the full spectrum of prompt–interaction dynamics, aligning with discriminative value and agency preservation. We further demonstrate the descriptive, discriminative, and generative powers of our entity set and relation set through systematically review existing interface design and proposing new variations in Secs. 4 and 5.

3.3 Atomic Paradigm Graph

Fig. 2 depicts the full interaction-augmented instruction model as a directed graph. However, considering the task-specific needs and the complexity of integrating all entities and relations, not all of them must be adopted to represent an individual interface. Therefore, we introduce the concept of an **atomic paradigm graph**, defined as a minimal, self-contained subgraph of the model that captures a single, coherent interaction paradigm (Table 2). Here, atomic means that GenAI (G) plays only one role within the paradigm (avoiding overlapping or conflated functions) and that the paradigm necessarily involves interaction (I), as paradigms without interaction fall outside our scope. Each atomic paradigm graph is constructed by sequentially selecting entities and relations in the order they are enacted, thereby encoding the workflow through which a tool supports human–GenAI communication. Accordingly, a concrete tool can be represented by one or more atomic paradigm graphs, depending on how many distinct paradigms it supports. For example, an advanced image editing interface with brush-based region selection (Table 2-P4) would add $H \rightarrow I \rightarrow A \rightarrow \text{Aug}$, and route the prompt through $T \rightarrow \text{Aug} \rightarrow G$, forming a richer paradigm [47, 52]. In another variant (Table 2-P8), if GenAI generates candidate widgets to further tune generated artifacts, the graph will include $G \rightarrow I$ (GenAI initiates widget interactions) followed by $H \rightarrow I \rightarrow A$ (human interacts with widgets to act on artifacts) [77]. These small structural differences capture the paradigm characteristics.

4 Design Paradigms

To examine if our IAI model can be generally applied to describe and differentiate existing designs, we revisited and annotated 66 GenAI system interfaces that combine prompts and interactions in human-GenAI communications. We found that all workflows can be represented with atomic graphs derived from the model, demonstrating its descriptive

Table 2. Taxonomy of atomic interaction paradigms in human-GenAI communication.

Interaction Timing	Starting Resources	Paradigm Name	Paradigm Description	Atomic Paradigm Graph	Related Tools
Interaction Before Calling GenAI	Prompt-only (no artifact at hand)	P1. Interactive Prompt Enhancement	Human selects parts of drafted prompts for GenAI to refine or expand content.		[1, 12]
		P2. Interactive Prompt Organization	Human organizes multiple text prompts into structured formats (e.g., tree) to fit the application.		[22, 27, 56, 84, 88]
		P3. Interaction as Instruction	Human's interactions outside artifacts are included with prompts for GenAI to operate on artifacts.		[35, 43, 92]
	Artifact-grounded	P4. Artifact as Instruction	Human directly manipulates artifacts, which are combined with prompts as GenAI instructions.		[19, 23, 46, 47, 52, 79]
Interaction After Calling GenAI	Prompt-only (no artifact at hand)	P5. AI-driven Prompt Suggestion	GenAI suggests new or extended prompts from the human's initial input for human selection.		[3, 4, 6, 13, 27, 49, 74, 81]
		P6. AI-driven Prompt Decomposition	GenAI restructures prompts into fine-grained, organized forms for interactive manipulation.		[14, 89]
		P7. Generative Prompt Control Widgets	GenAI generates interactive widgets for fine-grained prompt control.		[18, 27, 81]
		P8. Generative Artifact Control Widgets	GenAI generates widgets for humans to further manipulate or confirm artifact-related actions.		[19, 26, 32, 58, 73, 77, 83]
	Artifact-grounded	P9. Artifact to Organized Instruction	GenAI uses artifacts as starting points to generate structured prompts.		[27, 34, 90]
		P10. Artifact to Multimodal Instruction	GenAI parses and integrates artifacts to construct instructions.		[70]
		P11. Artifact-driven Prompt Enhancement	GenAI suggests actions based on contextual requests integrating artifacts and prompts.		[20]
		P12. Interactive Artifact Refinement	GenAI analyzes artifacts and initiates interactions based on prompts.		[76]

capacity to capture recurring paradigms. Furthermore, we identified 12 recurring atomic interaction paradigms, which effectively capture the similarities and differences between interfaces. It verifies our IAI model's power of differentiating interaction designs. We also hope that our identified paradigms can be a starting point for future interface design.

4.1 Revisit the Corpus

Data. We revisited prior corpus about interaction-enhanced GenAI interfaces [25, 30, 40, 48, 66] and filtered tools according to three criteria: (1) the system involves at least one GenAI model; (2) text prompts are supported as a communication channel; and (3) at least one other interaction modality (e.g., selection, brushing, sketching) is used to augment text prompts. Applying these filters yielded 66 representative system interfaces for analysis¹.

Annotation and Analysis. Following Sec.3.3, we decomposed each system interface into one or more atomic paradigm graphs (Fig.2) through manual annotation. During annotation, each atomic graph is instantiated by choosing the entities and relations the system interface implements, and by assigning sequence indices to relations to indicate the temporal or information-flow order. Concurrent flows receive the same index (e.g., when a user selection of artifact elements is incorporated into an augmented instruction simultaneously: H → I → A → Aug). Two authors jointly performed the annotation: each coded half the corpus, cross-checked the other's work, and resolved disagreements through iterative discussion until consensus was reached. Grounded in IAI model design (Sec.3) and definitions (Table 1), our annotation followed these principles:

- **AI atomicity.** Each atomic paradigm graph assigns GenAI a single, well-defined role to preserve atomicity and avoid ambiguity arising from multiple simultaneous AI functions.
- **Interaction requirement.** An atomic paradigm must involve at least one interaction modality; purely prompt-only workflows fall outside our scope.
- **Ordered relations.** Relations are numbered to encode the workflow order; relations that occur concurrently share the same index.
- **Iteration elision.** Repetitive iteration (e.g., multiple edit cycles with the same interaction design) is not re-annotated, as one representative cycle suffices to capture the paradigm's structural characteristics.

4.2 Atomic Paradigms

Using the IAI model as an analytic lens, we abstracted 12 recurring atomic paradigms (Table 2) from our corpus. We organize these paradigms along two orthogonal dimensions based on our model: (1) **interaction timing**: whether interaction (I) occurs *before* or *after* invoking GenAI (G); and (2) **user resources**: whether the user begins interacting with GenAI (G) when they have no artifact (A) at hand (*prompt-only*) or are in the *artifact-grounded* situation. The timing dimension roughly tracks intent clarity and control locus: pre-invocation interactions are typical when users can specify constraints up front, whereas post-invocation interactions support exploratory or ambiguous goals via mixed-initiative refinement. The resource dimension separates workflows where intent must be expressed solely in natural language from those where an existing artifact can be selected, annotated, or structured to ground the instruction. Below we analyze each of the four resulting classes as a coherent family of paradigms, and show how paradigm graph differences map to concrete tool behaviors via brief case comparisons.

4.2.1 Pre-invocation, Prompt-only: Structuring and Enhancing Prompts Before GenAI Invocation. This class groups paradigms (Table 2 P1-P3) where users begin with only prompts and seek to specify intent through pre-invocation

¹The complete annotation results: <https://interaction-augmented-instruction.github.io/>

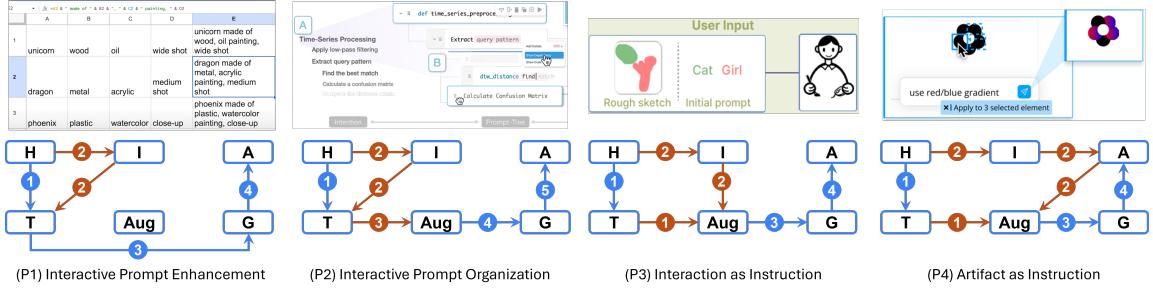


Fig. 3. Examples of pre-invocation paradigms, including prompt-only (P1-P3) and artifact-grounded (P4): (P1) Interactive prompt enhancement [1]; (P2) Interactive prompt organization [88]; (P3) Interaction as instruction [43]; (P4) Artifact as instruction [52].

refinement. Users typically have a clear goal and employ interaction to organize, extend, or transform textual instructions so that the ensuing generation aligns with their intent more precisely. For instance, a writer may elaborate a draft prompt with inline selection [57], or a programmer may decompose the prompt for a coding task into structured prompts for subtasks [22].

In all three paradigms (Fig.3 P1-P3), humans write prompts ($H \rightarrow T$) and GenAI produces artifacts ($G \rightarrow A$), yet they diverge in how to enhance the original natural language prompts (*i.e.*, refine T or construct Aug). The first paradigm, *interactive prompt enhancement* (P1), keeps the representation within the boundaries of natural language. User interactions just refine the wording of T ($H \rightarrow I \rightarrow T$), which is then executed directly. Dreamsheets [1], for instance, enables users to rapidly compose text prompt variations with a set of keywords through spreadsheet-like interactions for exploratory image generation (Fig.3-P1). While effective for quick iteration, it remains limited to text and cannot capture richer logical structures. In *interactive prompt organization* (P2), interactions introduce additional structure beyond natural language. The enriched representation, encoded as augmented instruction, integrates hierarchical or compositional logic before being passed to GenAI ($H \rightarrow I \rightarrow T \rightarrow \text{Aug}$). CoLadder [88] illustrates this by arranging prompts into a tree of subtasks (Fig.3-P2), while PromptChainer [84] links prompts in sequential chains. Yet even structured text has some limits; it presumes all user intent can be expressed linguistically. This gap is addressed by the third paradigm. *Interaction as instruction* (P3) encodes user actions themselves as operative intent, introducing non-linguistic signals in addition to text ($H \rightarrow I \rightarrow \text{Aug}; T \rightarrow \text{Aug}$). SketchFlex [43], for example, interprets freehand sketches on a canvas as executable instructions combined with prompts to guide expressive image generation (Fig.3-P3).

The key distinction lies in whether interaction only edits text prompts, introduces structured logic into augmented instruction, or adds non-linguistic information into augmented instruction. The interactive prompt enhancement paradigm (P1) emphasizes speed and lightweight iteration, while the prompt organization paradigm (P2) enables intent decomposition and traceability. Interaction-as-instruction (P3) broadens expressivity by moving beyond natural language altogether.

4.2.2 Pre-invocation, Artifact-grounded: Grounding Instructions in Existing Artifacts Before GenAI Invocation. This class (Table 2 P4) captures paradigms where users start with an artifact and specify intent through pre-invocation manipulation (*e.g.*, selection, brushing, sketching). It is also among the most common paradigms in existing systems. Typical scenarios include selecting a chart element to query [52], brushing an image region for editing [47], or highlighting code for debugging [5]. Here, interactions ground the prompt in concrete referents before generation.

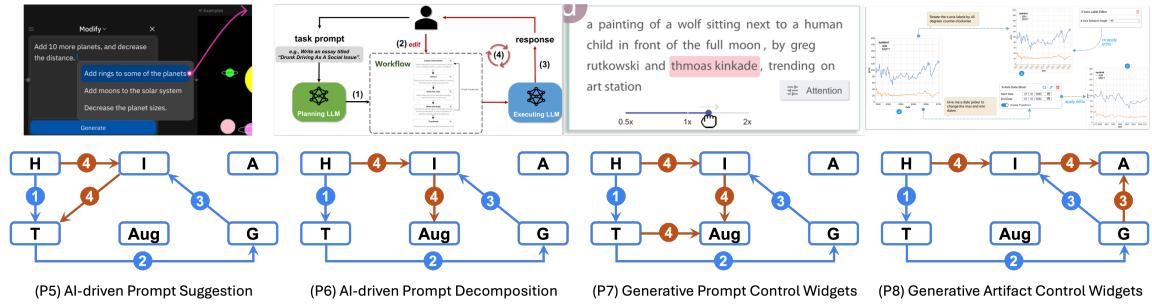


Fig. 4. Examples of post-invocation, prompt-only paradigms: (P5) AI-driven prompt suggestion [4]; (P6) AI-driven prompt decomposition [14]; (P7) Generative prompt control widgets [81]; (P8) Generative artifact control widgets [77].

In the *artifact as instruction* paradigm (P4), humans interact with artifacts to encapsulate partial or entire its content into augmented instruction ($H \rightarrow I \rightarrow A \rightarrow \text{Aug}; T \rightarrow \text{Aug}$). Systems such as DirectGPT [52] and MagicQuill [47] demonstrate this approach by passing dragged or brushed elements as precise constraints (Fig. 3-P4). At the first glance at DirectGPT, it might be confused with SketchFlex (Fig. 3-P3) as they both create visual augmented instruction with interactions for GenAI to operate on artifacts. However, with our paradigm graphs, it is easy to notice that the key difference lies in how augmented instruction is composed: DirectGPT, as a representative of the *artifact as instruction* paradigm, includes raw artifact segments, while SketchFlex, which belongs to the *interaction as instruction* paradigm category, encodes non-linguistic signals with interactions ($H \rightarrow I \rightarrow \text{Aug} \rightarrow G \rightarrow A$). This comparison highlights the key difference between the two paradigms: whether the interaction carries intent solely without embedding artifact.

The design difference shapes how intent ambiguity or unclarity is resolved. The *artifact as instruction* paradigm (P4) mitigates referential ambiguity by passing raw content to GenAI, whereas the *interaction as instruction* paradigm (P3) reduces descriptive effort by letting interactions themselves encode intent. For editing and debugging tasks, pre-invocation artifact-grounded interactions are particularly effective as they tie model operations to specific referents.

4.2.3 Post-invocation, Prompt-only: Iterative Prompt Steering After GenAI Invocation. This class (Table 2 P5-P8) captures cases where users specify intent solely through prompts, but do so *after* an initial GenAI invocation. Unlike pre-invocation paradigms, where intent is clarified before execution, here the process is fundamentally iterative: the first prompt triggers model output, and subsequent refinement occurs in response to what GenAI returns. Because each atomic paradigm centers on a single GenAI role, these workflows often do not emphasize artifact creation, but rather focus on AI-assisted prompt steering and iterative negotiation of intent. This class arises when users' initial instructions are vague, exploratory, or underspecified, and GenAI takes an active role in shaping subsequent prompts. Rather than users knowing exactly what they want, the system helps steer the process step by step.

The first three paradigms in this class (Fig. 4 P5-P7) share the basic flow $H \rightarrow T \rightarrow G$ (human writes text prompts to GenAI) and $G \rightarrow I$ (GenAI initiates interactions) but diverge in how AI-initiated interactions reshape subsequent instructions. In *AI-driven prompt suggestion* (P5), GenAI generates candidate refinements or alternative text prompts that users can adopt or edit ($H \rightarrow I \rightarrow T$), focusing on direct modification of natural language. Spellburst [4], for example, generates multiple auto-completed prompt suggestions by AI models. Then users can select one to guide subsequent calls (Fig. 4-P5). Similar to the extension from P1 to P2 (see Sec. 4.2.1), simple prompt refinement or suggestion by AI can hardly facilitate the needs for more structured intent communication. In *AI-driven prompt decomposition* (P6), GenAI externalizes its internal interpretation of a high-level prompt into a structured form such as a graph or task tree. Users

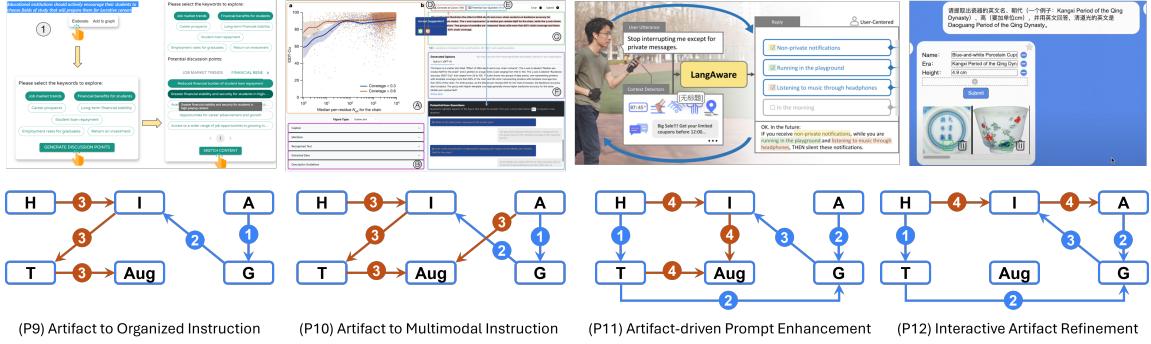


Fig. 5. Examples of post-invocation, artifact-grounded paradigms: (P9) Artifact to organized instruction [90]; (P10) Artifact to multimodal instruction [70]; (P11) Artifact-driven prompt enhancement [20]; (P12) Interactive artifact refinement [76].

then manipulate this representation directly ($H \rightarrow I \rightarrow \text{Aug}$), fragmenting, reordering, or parameterizing subtasks. Low-code LLM [14] and a recent work NeuroSync [89], exemplify this approach by visualizing inferred code-generation plans as editable graphs (Fig. 4-P6). These paradigms still operate primarily through text manipulation, finer-grained specifications remain difficult to express.

Furthermore, *generative prompt control widgets* (P7) extend prompts beyond natural language by having GenAI synthesize interactive controls. PromptCharm [81], for instance, generates sliders tied to text spans, enabling users to adjust their relative weights within a text-to-image prompt (Fig. 4-P7). A related but more hybrid paradigm is *generative artifact control widgets* (P8), where GenAI produces both an artifact and associated widgets that persist for subsequent manipulation. DynaVis [77], for example, augments visualization-oriented natural language interfaces with dynamic controls that let users iteratively adjust and replay edits with instant feedback (Fig. 4-P8). While P7 and P8 both involve model-generated widgets, their scope differs: P7 parameterizes *prompts*, extending intent specification, whereas P8 binds controls to *artifacts*, turning outputs into malleable, persistent interaction surfaces. This distinction demonstrates the discriminative power of the IAI model and connects directly to recent work on malleable UIs and GenUI [53], suggesting a trajectory where GenAI acts not only as a content generator but also as a co-designer of interfaces through which users iteratively shape intent.

These paradigms differ in where GenAI inserts initiative and how its proposals feed back into instruction. AI-driven prompt suggestion (P5) preserves the simplicity of textual prompts but accelerates exploration; decomposition (P6) reveals latent reasoning as manipulable structures, enhancing transparency and task management; prompt control widgets (P7) enrich prompt expressivity by exposing hidden parameters for direct control; and artifact control widgets (P8) extend this idea further by binding widgets to concrete outputs, enabling users to iteratively modify artifacts through persistent controls.

4.2.4 Post-invocation, Artifact-grounded: Interactive Editing and Clarification on Artifacts After GenAI Invocation. This class (Table 2, P9–P12) captures workflows in which an artifact—either produced by a prior GenAI call or provided directly by the user—serves as the anchor for subsequent interaction. Rather than relying solely on textual prompts, GenAI inspects the artifact, initiates interactions, and elicits user feedback to clarify or refine intent. Typical tasks include iteratively editing an image, interrogating a visualization, or correcting model-produced code.

The common structure is artifact-driven ($A \rightarrow G$), with GenAI initiating interactions ($G \rightarrow I$) that engage human responses ($H \rightarrow I$). The four paradigms differ in how these interactions shape the construction of follow-up instructions. In *artifact to organized instruction* (P9), GenAI analyzes the artifact, generates a set of candidate operations or reformulations, and presents choices that users select to compose a structured textual prompt. For example, VISAR [90] proposes expansion options for a selected paragraph; the user's choices produce a structured prompt tree for subsequent text generation (Fig. 5-P9). Building on this, *artifact to multimodal instruction* (P10) enriches the workflow by incorporating artifact itself. Here, GenAI extracts salient features from the artifact and asks users to tag or select them; the results are encoded into multimodal augmented instruction that combines artifact content with user intent as prompt. FigurA11y [70], for instance, extracts figure components and lets users link them to accessibility guidelines, producing a multimodal instruction (Fig. 5-P10). Moving beyond selection, *artifact-driven prompt enhancement* (P11) often positions the artifact as contextual grounding for semantic refinement. GenAI proposes contextual rules or mappings, which users confirm or modify in situ with interactions. LangAware [20] illustrates this by connecting low-level sensor signals to high-level contexts and enabling users to interactively combine contextual information with the original prompt before final execution (Fig. 5-P11). Finally, *interactive artifact refinement* (P12) emphasizes iterative analysis and correction. GenAI inspects the artifact in response to a prompt, surfaces candidate elements or annotations, and invites users to inspect, correct, or refine them. PDFChatAnnotator [76], for example, extracts information from PDFs and lets users guide annotation corrections interactively (Fig. 5-P12). Unlike prior paradigms, this focuses less on instruction construction and more on artifact-centered troubleshooting and refinement.

These paradigms address a recurring user need when users have existing artifacts: in the follow-up communication with GenAI, it might be cumbersome to fully write prompts by themselves (in P9 and P10) or to specify where or how operations should apply precisely (in P11 and P12). By leveraging GenAI for artifact resolution, these paradigms introduce mechanisms for grounded instruction generation or understanding. With these paradigms, users can confirm or change with interactions conveniently.

4.3 Cross-paradigm Insights and Suggestions

Taken together, the twelve atomic paradigms show how interaction timing and artifact availability jointly govern how user intent is expressed. Below we distill concrete design considerations for UI designers and GenAI researchers.

C1. Considering the timing for interaction and GenAI invocation based on intent clarity. Interaction timing indexes whether a task's intent is knowable up front (pre-invocation) or emerges through exploration (post-invocation). Pre-invocation paradigms assume the user can articulate explicit and clear intent in advance for generating or manipulating artifacts, such as clear coding structure and logic [22], or explicit image editing areas and tasks [47]. Post-invocation paradigms assume underspecified or exploratory goals: the system first initiates interactions to further clarify user intents [81] or produces outputs for steering and refinement [89]. Designers should align timing with the task's nature: employ pre-invocation paradigms for tasks requiring precision and auditable outcomes, but prioritize lightweight post-invocation paradigms when the goal is creative ideation and iterative refinement of an ambiguous intent.

C2. Grounding interactions with artifacts for referential intent. Instructions in natural language alone can be ambiguous (e.g., “make the flower brighter” without specifying which flower). The presence of an artifact shifts intent expression from purely linguistic descriptions to concrete, grounded references. By enabling users to select, highlight, or annotate artifact fragments, systems can reduce ambiguity and provide a stable foundation for commands [20, 70].

The consideration also aligns with design principles for AI-instruments by Riche *et al.* [60], where they proposed that text prompts should be grounded in other artifacts.

C3. Expressing and materializing intent with an appropriate form. In these design paradigms, a key design choice is how user intent is materialized to augment the original text prompt. The first way is to directly edit or extend the text prompt with interactions (Table 2-P1 and P5). An example is DreamSheets [1], where users can combine prompt fragments easily with interactions. It provides a simple and direct way to improve original prompts but lacks the power to cater complex intent, such as non-linguistic or referential intent. To handle more complex intent, an approach is to leverage interactions to introduce additional non-linguistic information to text and form augmented instructions, such as structural or parametric information (Table 2-P2, P3, P6, P7, P9 and P11). For example, CoPrompt [22] allows users to drag and drop prompt fragments to form a multi-level list of instructions. It materializes the non-linguistic intent expression in a convenient way with suitable interaction design. Regarding the referential intent, the key interaction is to link text prompts with artifacts and generate augmented instructions (Table 2-P4, P10). It addresses the challenges in describing the linkage between texts and artifacts by materializing users' intent with direct interactions on artifacts. Lastly, a unique case is to generate new interaction widget by text prompts and facilitate intent expression through direct manipulation (Table 2-P8, P12). GenAI creates reusable and persistent interactive widgets to materialize the meta intent and allows follow-up similar intent expression with simple interactions with widgets. A notable example is DynaVis. The meta intent like changing visual element colors can be materialized as a widget. The specific color to use can be directly selected by interactions. These different combinations of interactions and instructions provide a huge space to suit different intent expression and materialization. Beyond timing and artifacts availability, they serve as a key consideration for designers.

C4. Reusing, chaining, and innovating atomic design paradigms for adapting interaction design to new scenarios. Our summarized paradigms and the considerations C1-C3 above provide a concise mapping from task requirements to interface affordances. Designers can start from intent clarity and artifact availability to select appropriate paradigms for interface implementation. For example, they can use the pre-invocation, artifact-grounded paradigm (P4) for tasks that start from existing artifacts and demand precision. They can apply post-invocation, prompt-driven paradigms (P5-P8) for ideation and exploration. They should also consider the intent type as C3 mentions. Crucially, the twelve paradigms are not mutually exclusive: they can be flexibly combined and chained within a single application, enabling systems to shift fluidly between scaffolding, refinement, and repurposing workflows [27, 81]. Effective interfaces thus treat paradigms as composable building blocks rather than rigid templates, supporting diverse user needs. For example, IntentTagger [27] introduces small, atomic intent tags enabling micro-prompting and region-level edits, illustrating chaining and covering multiple paradigms (*e.g.*, P2, P4, P5, P7, P9). Reusing and chaining paradigms are not the end. Comparing the summarized paradigms and the entire IAI model, we can notice there are plenty of potential atomic paradigms that have not been explored. In future, interaction designers may start from existing paradigms to designing new ones for innovation.

5 Usage Scenario

The generative power of our proposed interaction-augmented instruction model and the twelve summarized atomic paradigm graphs extend beyond theoretical formulation and provides a practical design framework for human–GenAI communication [10]. This framework can guide both the iterative improvement of existing tools and the creation of Manuscript submitted to ACM

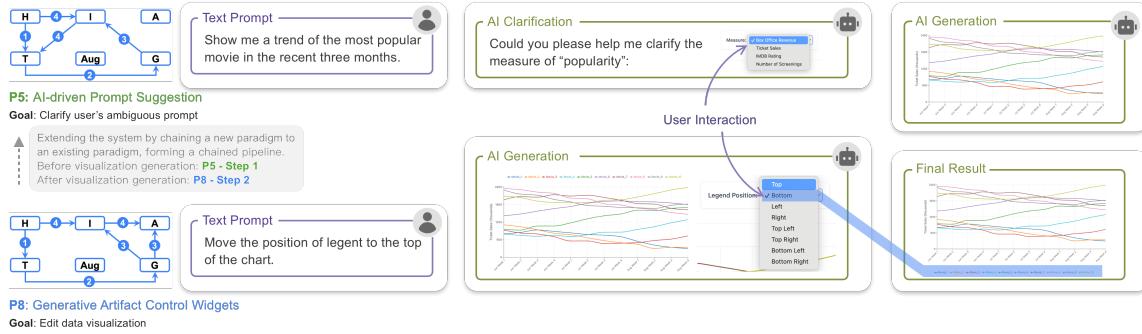


Fig. 6. Usage Scenario 1: Extending Pipelines through Chained Paradigm Graphs. For example, DynaVis [77] supports post-generation visualization refinement (P8). By chaining a pre-generation disambiguation paradigm (P5), the system can clarify ambiguous terms before execution, augmenting rather than replacing existing workflows.

novel interfaces tailored to emerging user scenarios. To illustrate the model’s applicability and impact, we present four usage scenarios to highlight how our approach can inspire, structure, and accelerate design decisions in real-world contexts, bridging the gap between conceptual models and actionable interface innovation.

5.1 Usage Scenario 1: Extending Pipelines through Chained Paradigm Graphs

One way our model supports innovation is by extending existing human-GenAI interfaces through the chaining of additional atomic paradigm graphs onto their current workflows (Sec.4.3-C4). This perspective treats current system interfaces not as static endpoints but as expandable foundations, where other paradigms can be strategically layered to address ambiguity, improve alignment, and ultimately enable more effective human-GenAI collaboration.

For example, when designing an ideal tool for data analysts to generate and edit visualizations, natural language can ease the burden of translating design requirements into initial visualizations, while graphical interactions can make subsequent adjustments and fine-grained editing more efficient. DynaVis [77] (Fig.4-P8) illustrates this synergy by augmenting natural language interfaces with dynamic widgets that support iterative refinement. Yet, at the same time, early-stage ambiguity in user intent often remains a challenge. Fig.6 illustrates this, imagine a data analyst at a movie company exploring market trends for the second quarter across U.S. cinemas. The analyst might ask: “*Show me a trend of the most popular movie in the recent three months.*” Directly generating data insights to such fuzzy user questions (e.g., “the most popular”) may not fully align with the user’s intent, frequently leading to time-consuming post-generation refinements. Using the IAI model and the atomic paradigm graphs, system designers can find and introduce a pre-generation disambiguation paradigm (P5, AI-driven Prompt Suggestion) before P8. Instead of immediately generating a visualization, the system could first initiate a clarification step, asking the analyst what “popular” should mean in this context, by ticket sales, IMDB rating, box office revenue, or number of screenings. This step structures the workflow to clarify ambiguous prompts upfront, improving alignment, reducing back-and-forth iterations, and making subsequent widget-driven refinement more precise.

By enabling such chaining, the Interaction-Augmented Instruction model does not replace existing workflows but augments them, making human-GenAI collaboration more user-friendly, accurate, and adaptable to nuanced tasks.

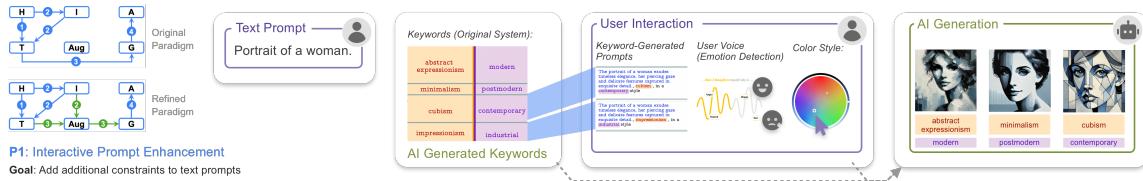


Fig. 7. Usage Scenario 2: Refining Paradigms by Adjusting Graph Structures. For example, Dreamsheets [1] (P1) can be extended by adding $I \rightarrow Aug$, introducing multimodal inputs (e.g., voice for emotion, palette for color tone) beyond text prompts. This enables more structured, controllable, and user-steerable exploration.

5.2 Usage Scenario 2: Refining Paradigms by Adjusting Graph Structures

In addition to strengthening workflows at a macro level by chaining different paradigms, the flexibility of the relations among entities in the IAI model also enables micro-level edits within a single paradigm. Such refinements can be realized by adjusting the relations among entities in existing paradigms to improve precision and control.

Take the example of AI artwork creation. In media-art contexts, user intent often extends beyond describing the content of an artwork to include more nuanced dimensions, such as conveying emotion, which is an aspect that is difficult to express through text alone and is often better captured through other modalities like voice [54] and facial expression [28]. Dreamsheets [1] (Fig.3-P1) provides a strong foundation in this scenario: its spreadsheet-like interactions make prompt refinement and enhancement efficient for rapid iteration in artwork generation and exploration (P1, Interactive Prompt Expansion). Yet, relying solely on natural language refinement can still be limited in aligning with a user’s intent, as analyzed based on the IAI model in Sec.4.2.1. For example, even a seemingly simple adjustment, such as changing the color style, becomes cumbersome when users must come up with the precise name of the desired style for prompting AI. Also, users must rely on texts to describe their nuanced feeling (e.g., emotion) to AI.

Using the IAI model, interface designers can systematically identify potential links to enhance Dreamsheets in its corresponding paradigm graph P1. Specifically, an addition of a relation from interaction to augmented instruction ($I \rightarrow Aug$) can provide additional intent expression methods beyond natural language. As shown in Fig.7, in practice, this adjustment could introduce additional interactions for specifying global artwork parameters. For instance, after rapidly generating prompt candidates for a “*portrait of a woman*” through spreadsheet-like interactions, the user may specify their feeling in creation via voice, where their emotion can be detected. The user can also adjust the overall color tone using a palette. This interface refinement transforms free-form prompt expansion into a more systematic, user-steerable process with an augmented instruction. It enables more targeted and expressive exploration through appropriate materialization of user intent (Sec.4.3-C3).

5.3 Usage Scenario 3: Applying the IAI model to Emerging Scenarios

A distinctive strength of the IAI model lies in its generative capacity: by formalizing six core entities and their relations, the model can guide system designers in deriving atomic paradigm graphs for new human-GenAI applications. This process is especially valuable in the emerging scenario of multi-agent workflows, which often fall short of supporting fine-grained iterative refinement.

Consider Data Director [64], a multi-agent system that automatically generates animated data videos from data tables with agent roles such as Data Analyst and Designer (Fig.8). Although such end-to-end automation can rapidly deliver initial outputs, its results often require follow-up refinement by humans. For example, in the case study of stock price analysis, after generating a data video with an animated line chart of multiple companies and corresponding

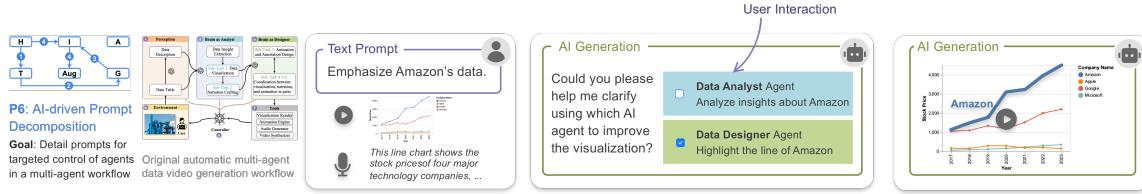


Fig. 8. Usage Scenario 3: Applying the IAI Model to Emerging Scenarios. For example, in a multi-agent system for animated data videos [64], the IAI model guides the integration of user feedback for iterative refinement. This yields a paradigm aligned with P6 and demonstrates the IAI model can serve as a reasoning tool for emerging scenarios.

narration, the user may issue a follow-up instruction: “*Emphasize Amazon’s data.*” How might the system designer extend the existing multi-agent workflow to accommodate this new requirement?

Using the IAI model, the system designer begins by identifying the relevant entities: Human (H), Text Prompt (T), Generative AI (G), and Interaction (I), where Generative AI is to understand the user’s fine-tuning instruction and refine the initial prompt in the multi-agent system. Next, the system designer specifies the relations required to fulfill the user’s intent. First, the human issues the request ($H \rightarrow T$). In this multi-agent system, producing a data video involves multiple tasks such as extracting insights, generating visualizations, crafting narration, and creating animations or annotations. Accordingly, a single instruction may map to different agent actions, such as the Designer agent animating Amazon’s line or the Data Analyst agent focusing on Amazon’s insights to craft narration. To ensure agent-specific accuracy, GenAI decomposes the text prompt and proposes candidate actions by different agents ($T \rightarrow G, G \rightarrow I$), and the human then reviews and confirms these suggestions ($H \rightarrow I$). Thus, at this scenario, the interaction occurs *after* calling GenAI (Sec.4.3-C1) and involves a text-only starting resource (Sec.4.3-C2), consistent with the “Post-invocation, Prompt-only” category (Sec.4.2.3). Finally, the confirmed interaction forms a new augmented instruction ($I \rightarrow Aug$), which is passed back for another round of GenAI calling (chained by another follow-up paradigm).

This design process yields a paradigm that aligns with P6, AI-driven Prompt Decomposition. By explicitly modeling entities and relations, the IAI framework helps system designers localize where and how human input should occur, and how to derive paradigms to support iterative communication between humans and AI. More broadly, this case demonstrates how the IAI model can serve as a reasoning tool for emerging scenarios: starting with entities, constraining relations along the two axes of interaction timing and user resources (Table 2), and applying cross-paradigm insights (Sec.4.3) to guide concrete design choices.

5.4 Usage Scenario 4: Deriving New Atomic Paradigm Graphs

Beyond applying the IAI model to new usage scenarios, its generative capacity also enables HCI researchers to hypothesize and explore new paradigms of human-GenAI collaboration. While the twelve atomic paradigm graphs we distilled capture a representative set of existing practices, they do not exhaust the design space. In this case, we take the reverse perspective: rather than deriving paradigms from scenarios, we start by modifying existing paradigm graphs to see how such changes may give rise to new paradigms and, in turn, novel application scenarios.

Consider the paradigm P11, Artifact-driven Prompt Enhancement (Fig.5-P11), where GenAI initiates interactions based on information from artifacts (contextual information) and human prompts. Contextual information is critical in many scenarios, such as embodied AI in everyday life. But instead of the human initiating the conversation based on context like P11 (starting from $H \rightarrow T$), what if the **AI initiates the conversation proactively**, as illustrated in Fig.9 (left) and exemplified in Fig.5-P9 and P10 (starting from $A \rightarrow G$)?

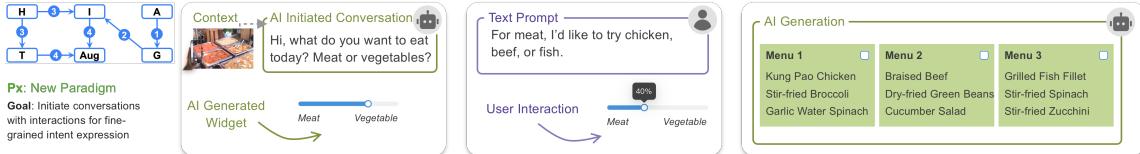


Fig. 9. Usage Scenario 4: Deriving New Atomic Paradigm Graphs. For example, modifying P11 suggests a new paradigm where AI proactively initiates interaction. In a canteen scenario, an assistant proposes menu options through contextual sensing and interactive widgets, illustrating how paradigm modifications can inspire novel applications.

Assume an individual enters a canteen and inspects the available dishes, the human–AI conversation is not initiated by the human through an explicit prompt (Fig. 9). Instead, an embodied AI assistant (e.g., embedded in AR glasses or a mobile app [33, 82]) proactively perceives the environment (Sec. 4.3-C2), cross-references it with the individual’s dietary history, and initiates the interaction: “*Hi, what do you want to eat today? Meat or vegetables?*” Alongside this query, the system also generates an interactive widget (e.g., a slider) for specifying a preferred proportion of vegetables versus meat. Suppose the user selects 60% vegetables and 40% meat, and adds: “*For meat, I’d like to try chicken, beef, or fish.*” The AI then integrates this input with the detected canteen offerings to recommend a personalized list of top dishes. This new graph and usage scenario foregrounds **AI-initiated, context-aware interaction**, expanding the design space toward more proactive and situated human–GenAI collaborations (Sec. 4.3-C4), and more broadly, opening up fundamentally new paradigms of communication.

6 Discussion

This section reflects our research (Sec. 6.1) and outlines future directions (Sec. 6.2).

6.1 Reflection

Why do we need instruction-augmented interaction? We model the interplay between prompts and interactions because GenAI systems increasingly rely on both, yet lack a framework to make their complementarity explicit. The IAI model and the twelve atomic paradigms articulate a core claim: prompts and focused interactions are complementary (not interchangeable) modes for externalizing user intent. Treating Augmented Instruction (Aug) as the explicit input to generative models foregrounds a functional separation: Text Prompt (T) supplies high-level, abstract goals; Interaction (I) supplies precise, referential constraints and grounding. There are three closely related reasons this interplay is necessary. First, generative models map underspecified instructions to a broad set of plausible outputs [60]; interaction signals collapse referential ambiguity and materially improve the likelihood of a targeted, single-turn outcome [61]. Second, interactions encode provenance and manipulable constraints that support fine-grained control properties that language alone cannot reliably provide at scale [69]. Finally, the IAI model brings human–GenAI communication closer to human–human interaction. In practice, people rarely rely on language alone; they complement speech with gestures, sketches, and shared artifacts to ground intent. By mirroring these multimodal practices, IAI reduces ambiguity and enriches expression, pointing toward GenAI systems that act as more natural collaborators in human–AI co-creation.

How should we apply interaction-augmented instructions? Adopting interaction-augmented instructions implies several foundational shifts in human–AI practice. First, expertise will shift from prompt engineering to instruction design. Users should compose reusable and multimodal instructions rather than optimizing text alone, while tools need to expose these capabilities with clear discoverability to support effective use [71]. Second, cognitive load and UX

trade-offs must be managed: interactions can reduce text specification but add interface complexity, so designers should prioritize low-friction affordances (e.g., defaults, progressive disclosure, previews) to minimize overhead [72]. Third, evaluation can broaden beyond artifact quality to include axes that follow directly from the IAI distinction, such as correctness of local changes tied to interactions (referential fidelity), rounds to satisfactory output (convergence cycles), ease of steering behavior (controllability), and user comprehension of influences (provenance clarity).

What can our model contribute to interaction-augmented instructions? The IAI model contributes to both engineering practice and HCI theory-building. For practitioners, paradigm graphs serve as a design language that makes implicit design trade-offs explicit. Developers can compare alternatives, identify unexplored regions of the design space, and refine existing interfaces by recombining atomic paradigms. This resonates with prior calls to move beyond ad-hoc demonstrations toward systematic design frameworks in HCI [9]. For researchers, our model complements prior taxonomies [25, 30] and principle-based approaches [60] by introducing a formal representational structure that captures both entities and relations in human–GenAI workflows. Such formalization enables cumulative comparison across systems and provides a substrate for analytical and generative methods, similar to how prior models advanced earlier eras of HCI [8, 15, 16].

6.2 Future Work

Model: Extending the IAI Model. The IAI model intentionally abstracts at a high level to capture the interplay between text prompts and interactions. This abstraction aims for generality, but extensions can enrich the model for more fine-grained analysis of specific design questions. At the entity level, entities can be refined or expanded to capture richer system dynamics. For instance, as noted in Sec.3.1, while *context* is currently subsumed under the *artifact* entity, making it explicit would support the analysis of how retrieval-augmented systems use user provenance. In addition, the “human” entity could generalize into an *actor* role, instantiated by either humans or AI agents, enabling representation of mixed-initiative or multi-AI agent workflows [41, 72]. At the level of relations, finer distinctions can also sharpen analysis. For example, the link from *interaction* to *augmented instruction* manifests differently across tools, ranging from sliders and widgets to sketching or structured graph editing. Making such variations explicit would not only capture existing diversity but also open design opportunities, such as composable augmented instruction libraries for domain-specific workflows [62], adaptive timing of system responses [24], or model-assisted widget generation [17].

Paradigm: Iterative Expansion of Paradigms and Next-Generation Scenarios. The twelve atomic paradigms are not exhaustive but serve as a core library for iterative growth. Expansion occurs iteratively along multiple paths, as illustrated by our four usage scenarios (Sec.5). Paradigms can be extended by *chaining* additional graphs onto existing workflows (Scenario 1), *refined* through structural adjustments to better materialize user intent (Scenario 2), *applied* to emerging domains to guide design reasoning (Scenario 3), or even *modified* to hypothesize entirely new paradigms that inspire novel applications (Scenario 4). These scenarios illustrate how atomic paradigms function as both descriptive lenses and generative building blocks, capturing current practices while revealing underexplored design subspaces. Looking ahead, next-generation contexts will further expand the paradigm space. XR brings gaze and embodied gestures [29]; cross-device and multimodal workflows demand seamless orchestration [38]; adaptive systems restructure interfaces dynamically [87]; and affective computing raises questions of how emotion should shape interaction. Our model is extensible to these futures by augmenting paradigm graphs with new entities and relations, offering a systematic scaffold for both incremental refinement and paradigm-level innovation.

Interface: From Paradigms to Generative Design. The IAI model is both descriptive and discriminative, as well as generative. It decomposes hybrid system interfaces into atomic paradigm graphs, while discriminatively highlights structural differences across interfaces. Generatively, paradigm graphs serve as design blueprints [10], guiding the refinement of existing interfaces and the creation of new ones. Our usage scenarios (Sec.5) illustrate this generative role in practice, showing how paradigm graphs can inspire novel interface designs for various application scenarios. They demonstrate how paradigm graphs not only capture existing practices but also scaffold systematic innovation. Beyond manual application of these paradigm graphs, we envision that it can also inspire UI generation. For example, based on user intent clarity and the availability of artifacts (Sec.4.3), AI models can select suitable paradigms and generate adaptive interfaces to guide users for next round of communication.

7 Conclusion

We introduced the Interaction-Augmented Instruction (IAI) model that formalize how natural language prompts and GUI interactions jointly shape human–GenAI communication. With the IAI model, we summarized twelve atomic paradigms based on existing tools, which provide reusable abstractions that enable systematic characterization, comparison, and innovation in interface design. Our usage scenarios demonstrate how this model and the extracted twelve atomic paradigms bridge conceptual models with actionable design choices, supporting refinement of existing tools and exploration of new interaction spaces. The paradigms and usage scenarios jointly verify that our proposed IAI model have sufficient descriptive, discriminative, and generative power to model the interplay of prompts and GUI interactions. In future, we plan to further explore this research direction through extending the model to finer granularity, expanding the collection of paradigms, and exploring more usage scenarios for the model and paradigms, such as generative UI.

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