èkphrasis

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Èkphrasis Reimagined: the Impact of AI on Interpretation and Generative Meaning

Lorenzo Ceccon
Matteo Cavaglià

Abstract

This study examines the transformation of *èkphrasis* in the digital era, specifically regarding artificial intelligence AI-powered generative systems. *Èkphrasis*, originally defined as a vivid verbal representation of visual art, has transcended its classical rhetorical and literary roots to encompass transmedia applications facilitated by computational technologies. The research examines how AI-mediated text-to-image generation alters ekphrastic practice, shifting from descriptive narration to a process of interpretative co-creation between human users and Machine Learning models. Generative AI, through probabilistic associations and multimodal synthesis, challenges conventional notions of artistic agency, requiring a reevaluation of the relationship between linguistic input and visual depiction. This paper analyzes the balance between descriptive and evocative language in AI prompting, highlighting the influence of algorithmic biases, latent-space dynamics, and iterative refinement in creating an interactive ekphrastic framework. Ultimately, it argues that AI-assisted ekphrasis transcends traditional boundaries of textual and visual interpretation, positioning itself as a creative, curatorial, and computationally mediated process of meaning production, where the role of the human creator is centred in taking responsibility for the guidance towards, and selection of, the final outcome based on his/her creative vision.

Keywords
Èkphrasis, Generative AI, Text-to-image translation, Multimodal communication, AI-assisted creativity.

AI-generated visualisation showcasing the application of *èkphrasis* through artificial intelligence (image by the authors).

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Introduction: searching for a definition for *èkphrasis*

In introducing her work, Zeitlin describes ekphrasis as a slippery concept, highlighting the difficulty in defining the concept [Zeitlin 2013]. Indeed, any attempt to outline the nature of *èkphrasis* reveals a wide range of interpretations. This apparent vagueness should not be mistaken for inconsistency; rather, it underscores the conceptual flexibility and enduring utility of *èkphrasis* as a cognitive and artistic tool, adaptable across historical and contextual shifts. *Èkphrasis* can be defined as a rhetorical exercise [D'Angelo 1998], a literary genre [Scott, 1991], or even a poetic technique [Zamani, Alavijeh 2024]. However, all uses commonly trace ekphrasis to its ancient Greek origins, where it denoted the vivid verbal depiction of visual phenomena. Though often linked to descriptions of artworks, its historical application, as Chinn notes, encompassed any visually perceptible subject conveyed through evocative language [Chinn 2007]. The use of evocative description is widely recognized in literature as essential. Zeitlin identifies three core qualities: enargeia (vividness), sapheneia (clarity), and phantasia (mental imagery), which together serve to elicit in the audience a natural sense of the visual and emotional presence of the described subject [Zeitlin 2013]. While originally emerging as an oral device, *èkphrasis* gradually evolved into a written practice, mirroring broader cultural and communicative transformations across the ages [Lara-Rallo 2012].

In addition, *èkphrasis* not only conveys meaning but also generates new insights by translating visual stimuli into language. This process enables a reinterpretation of the visual, allowing descriptive language to reveal emotional, symbolic and conceptual dimensions often implicit in the visual experience. This aspect is of particular interest in the digital age, where *èkphrasis* evolved into a transmedia practice [Jansson 2018].

Media traditionally refers to the collective set of tools and communication channels available to a society for transmitting information. This includes both spoken and written language, as well as visual representations and other forms of expression [Haghshenas 2017]. The evolution of digital technologies has rendered the relationship between *èkphrasis* and media increasingly dynamic. In the digital age, AI, particularly through natural language processing, has introduced new forms of ekphrastic engagement, enabling users to generate textual descriptions of images, videos, and artworks [Bajohr 2024].

The integration of AI raises important questions about the nature of communication with non-human actors. For example, when engaging with generative AI technologies, humans perform a 'dialogue' with the machine. But does this interaction need to be evocative and vivid, or is it enough to remain functional? Is human-machine communication limited to machine-oriented instructions, or can it allow for expressive, poetic language? And in turn, should programmers draw inspiration from the artistry of poetry?

Generative-AI and multi-modal communication

In AI-driven systems, generative AI represents a subset of applications designed to create specific types of content based on user input. These platforms can generate text, images, sound, video, computer code, and other forms of media by leveraging Machine Learning models trained on vast datasets [Chalamayya Batchu Veera Venkt 2024]. Generative AI platforms are software applications that create content by learning patterns from an initial dataset through training. Unlike traditional rule-based systems, which follow predefined instructions, generative AI produces outputs without directly manipulating the original material [Ramdurai, Adhithya 2023]. Instead, it infers an appropriate statistical distribution (a distribution of words if the requested output is text, or pixel colours if it is an image) from training data to create new, contextually relevant outputs. In this regard, the training process involves adjusting the model's parameters to recognize and replicate the structural and compositional patterns within the data, rather than memorizing or reproducing exact examples [Goodfellow *et al.* 2014]. The most popular way to instruct a generative model is through a textual description, commonly known as a prompt. A prompt is essentially an instruction compiled with the intent of detailing,

or suggesting, the desired output [Torricelli *et al.* 2024]. Creating a prompt requires the user to engage in mental ekphrasis, translating a mental image or concept into a coherent description. This serves as a bridge between the user's envisioned outcome and the AI's capacity to generate it. The system then interprets the description, performing a transmedia translation that transforms the text into a corresponding medium, such as a visual representation. This process is shaped by the model's programming, training data, and learning strategy, with the final output reflecting the dynamic interaction between human intent and machine capability. The practical use of a prompt is defined by several properties. Primarily, the vast number of variables involved makes it impossible for the user to predict the final outcome with certainty. As a result, the outcome can only be 'guessed', and until the instruction is executed, the prompt remains potentially linked to multiple, potentially infinite, outcomes (fig. 1).

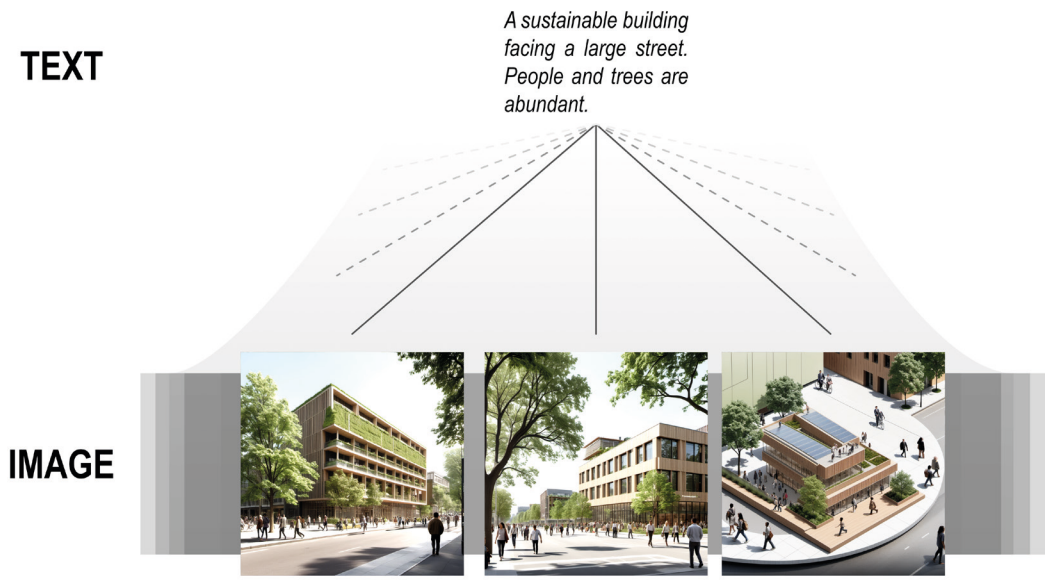

Fig. 1. If multiple images are similar to one another, it is possible that the textual description of one may match all of them.

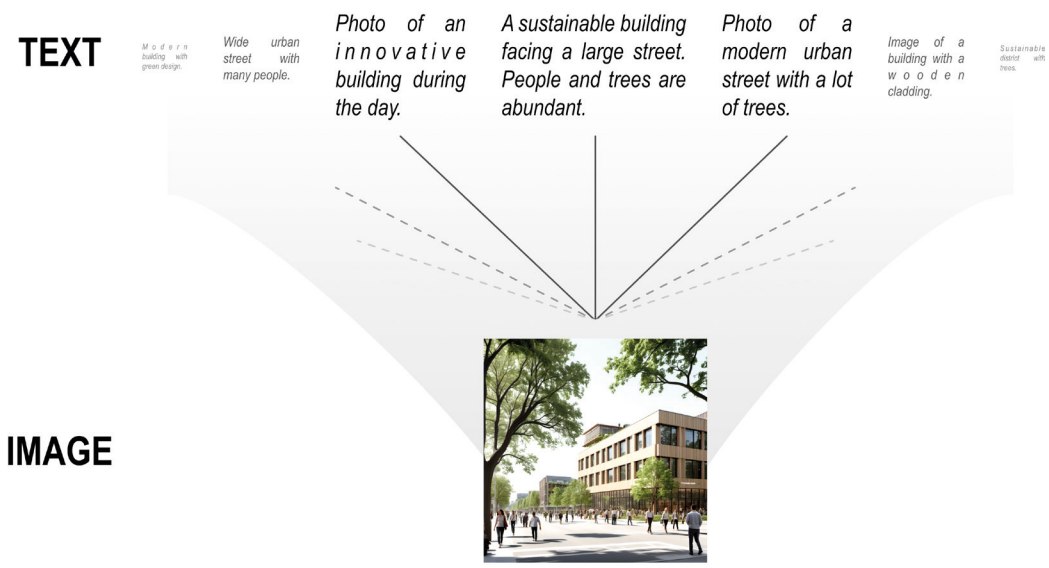

Fig. 2. An image can be described in many ways, making the task of creating a fitting description one of selecting a single option from many.

Conversely, a specific mental image can be linked to an infinite number of prompts, each offering a different framing of the desired outcome, with varying levels of detail and focus (fig. 2). This creates an explorative space of creative divergence, where navigating through different prompts leads to a range of potential outcomes (fig. 3). The exploration of multiple possibilities via AI is currently a highly active trajectory of research. Numerous studies have observed how AI implementation can rapidly generate a diverse array of results, extracted by mapping these 'possibilities' through variations in the prompt and other variables (Cai *et al.*, 2023). This dynamic exploration allows for a rich diversity of outcomes, but finding a clear, consistent strategy to approach a single goal remains an open question.

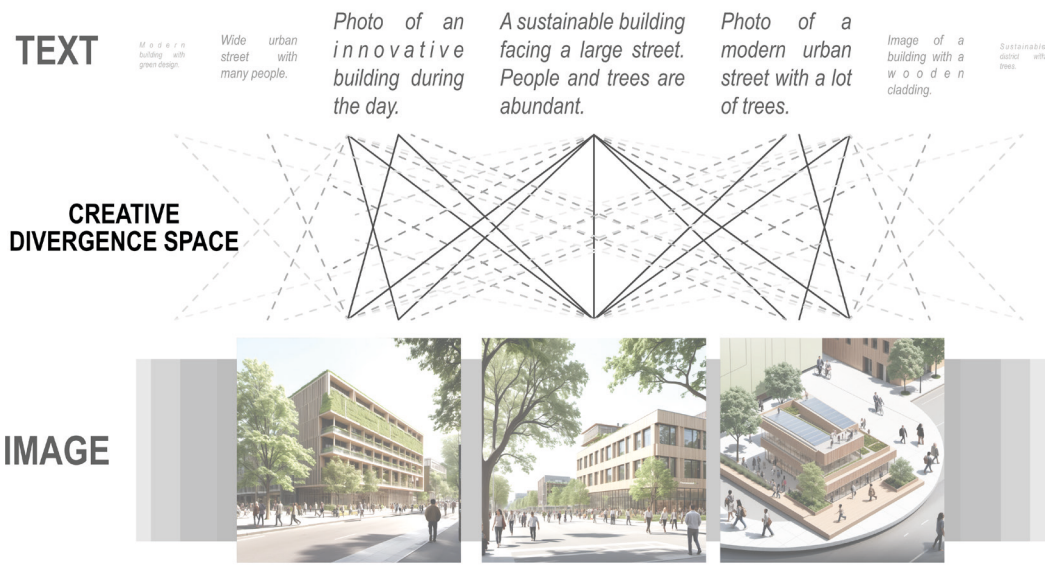

Fig. 3. The potential correlation between images and descriptions creates a network of possibilities, where multiple instances can be connected with varying degrees of fitness.

Evocative *vs.* descriptive: the role of language in generative AI and *èkphrasis*

Èkphrasis, in its classical form, has always balanced evocative and descriptive elements to render a visual experience through words. Traditional ekphrastic texts oscillate between objective descriptions (prescriptive-descriptive) and subjective, interpretative evocation (evocative). In classical rhetoric, descriptive ekphrasis follows a structured, quasi-instructional format, detailing spatial relationships, compositional elements, and material properties [Krieger, Krieger 2019]. Evocative ekphrasis, on the other hand, elicits moods, emotions, and symbolic resonances, engaging the reader in a cognitive and affective reconstruction of the depicted scene [Rippl 2015]. In generative AI, the distinction between different textual inputs is crucial, as they produce varied machine-generated visual outputs. Unlike Visual Programming Languages (VPLs), where explicit procedural rules generate geometric forms with minimal semantic ambiguity, generative AI models interpret textual descriptions in a highly open-ended manner [Manovich, 2019]. VPLs (e.g., *Grasshopper*, *Houdini*) rely on strict, deterministic rules, ensuring that each instruction produces a consistent outcome. In contrast, generative AI (e.g., *DALL·E*, *Stable Diffusion*) functions non-deterministically, generating a range of possible images from loosely defined prompts through latent-space pattern matching [Radford *et al.* 2021]. While VPLs yield predictable results unless intentionally randomized, generative AI operates probabilistically, where outputs are influenced by statistical associations, training biases, and latent representations (table 1).
Prompting AI presents the challenge of navigating an uncertain interpretative space, where evocative language generates a range of possible meanings rather than fixed signification. Unlike procedural scripting, which operates within explicit parameters, AI prompting relies on inference, requiring users to anticipate and adjust for the model's latent biases [Basso Fossali

FRAMEWORK	MODE OF INTERPRETATION	OUTCOME PREDICTABILITY	SEMANTIC PRECISION
Visual Programming (e.g., Grasshopper, Houdini)	*Deterministic, rule-based generation*	*Fixed, precise outcomes*	*Certain*
Generative AI (e.g., DALL·E, Stable Diffusion)	*Probabilistic, associative meaning-making*	*Fixed, chaotic outcomes*	*Variable*

Table 1. Procedural *vs.* probabilistic interpretation in AI.

et al. 2022]. The process of iterative refinement, where users modify prompts based on prior AI-generated outputs, mirrors an emergent, heuristic-based interaction model rather than a procedural scripting paradigm [Herman, Hutka 2019].The iterative nature of prompt refinement further emphasizes the probabilistic structure of AI-assisted ekphrasis, where meaning is dynamically reshaped through linguistic modification rather than static textual description.
Thus, AI-assisted èkphrasis does not 'describe' an image but instead computationally generates visuality, marking a fundamental departure from traditional ekphrastic practices. The role of the human user shifts from descriptive narration to curatorial intervention, requiring a new literacy in AI-human creative collaboration.

Generative AI as a mirror of human representation: *èkphrasis* and mental modelling

Historically, *èkphrasis* has been viewed as a reconstructive and imaginative process in which the describer mentally visualizes an object, scene, or concept before verbalizing it. This process involves complex cognitive faculties that shape both perception and representation. As such, the study of *èkphrasis* often intersects with the domain of graphical representation, suggesting that graphical processes may influence thought, and vice versa. Notably, as studied by Van Meter and Firetto [Van Meter, Firetto 2013] and Fan *et al.* [2023], the production of graphical content is not isolated from an individual's past and present experiences (fig. 4). Both the immediate perception of the graphical act and the person's cognitive and cultural background can equally influence the outcome. Building on this perspective, this study explores how the cognitive processes required to create ekphrasis, understood as a means of engaging with a mental image, may be influenced by similar factors as the ones at play in the production of graphical content:
- *Weltanschauung* (worldview): the individual's cultural, perceptual, and conceptual framework, which influences what is considered meaningful or visually salient [Rippl 2015];
- memory integration: the retrieval and synthesis of past visual experiences, shaping how objects, textures, and spatial arrangements are recalled and reconstructed [Herman, Hutka 2019];
- motor representation: in traditional artistic practices such as drawing or painting, sensorimotor skills play a fundamental role in translating mental images into tangible forms [Herman, Hutka 2019];
- iterative feedback loop: the act of creating visual representations dynamically modifies the artist's perception, leading to continuous refinement and adaptation of the mental image based on the representation being produced in real time.
These interwoven cognitive functions ensure that human-generated representations, whether written or visual, reflect experiential and interpretative depth. However, when prompted by AI rather than a human artist, this cognitive flow shifts from an embodied, perceptual process to a computationally mediated transformation:
- the human user no longer translates a mental image into hand-drawn strokes but instead encodes it linguistically, relying on descriptive or evocative textual prompts;
- the AI interprets the prompt based on its training dataset, learned biases, and latent space associations, rather than personal or sensory experience [Radford *et al.* 2021];
- instead of a sensorimotor-driven drawing process, the AI maps textual signifiers to probabilistic visual outputs, generating statistically interpolated representations rather than intentionally structured compositions [Boyack, Klavans 2010].

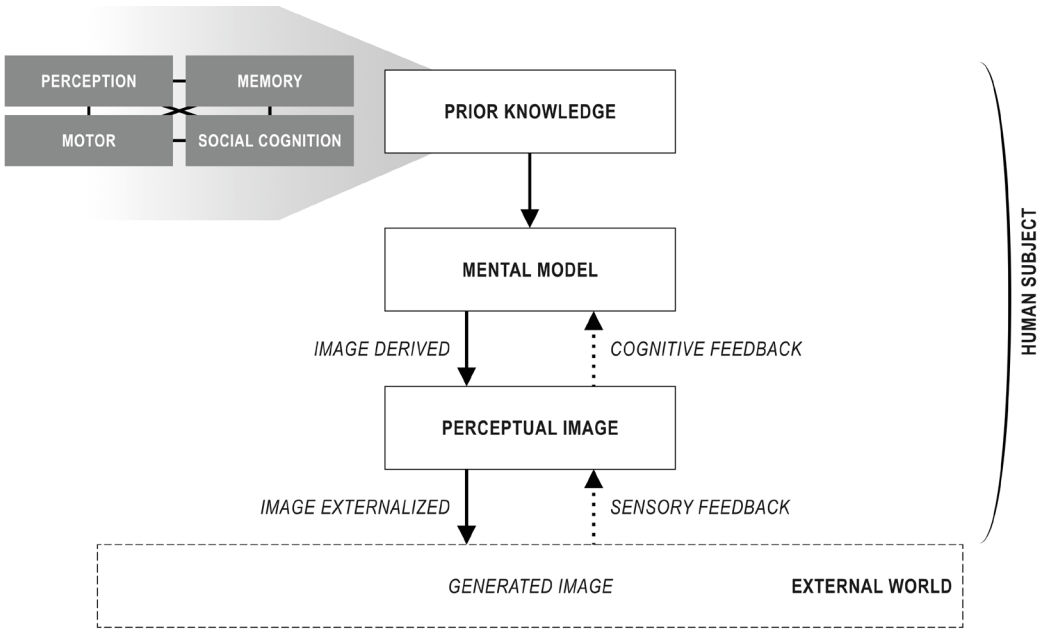

Fig. 4. The cognitive model of mental representation and image generation, showing the relationship between prior knowledge, mental models, perceptual imagery, and externalized images.

The computational 'mirror' of mental representation

In this sense, AI's response mirrors –but does not replicate– the human ekphrastic process. While both involve a transformation from textual input to visual representation, they differ fundamentally in how meaning is generated and refined (table 2).

A crucial implication of this computational transformation is that AI-generated ekphrasis does not possess intentionality, imagination, or a self-reflective conceptual framework. Instead, it synthesizes visual outputs based on prior statistical exposures, meaning that its semantic reach may exceed or deviate from the conceptual scope envisioned by the human prompter [Radford *et al.* 2021]

This deviation has two key consequences:

1. Expansion of Semantic Scope - The AI-generated images may introduce unexpected conceptual associations, drawing from patterns and relationships that the human user did not explicitly encode in the prompt. These emergent outputs challenge the assumption of a direct correspondence between verbal description and visual realization, highlighting the latent biases and generative tendencies within AI models [Boyack, Klavans 2010].

COGNITIVE STAGE	HUMAN REPRESENTATION (DRAWING & PAINTING)	AI-GENERATED REPRESENTATION (PROMPTING)
Input Mechanism	*Mental model based on perception, memory, and learned artistic techniques*	*Linguistic encoding interpreted through statistical latent space*
Translation Mechanism	*Sensorimotor execution (hand-drawn strokes, color selection, compositional adjustments)*	*Algorithmic pattern matching (mapping text tokens to visual data points)*
Feedback and Iteration	*Continuous refinement through real-time perceptual adjustments*	*Iterative prompting to refine semantic ambiguity and output coherence*
Interpretative Control	*Artist actively governs meaning through personal skill and conceptual intent*	*AI selects probable outputs based on dataset distributions, with partial opacity in generative logic*

Table 2. A comparison between human cognitive representation and AI-generated representation in *èkphrasis*.

2. Iterative Correction - Since AI operates probabilistically, users must act as curators, refiners, and interpreters, adjusting the terminology, structure, and specificity of their prompts through an iterative refinement process. This mirrors the feedback loops of traditional artistic creation, albeit mediated through linguistic adjustments rather than sensorimotor adaptation [Herman, Hutka 2019].

AI-driven *èkphrasis* introduces an additional layer of interpretative mediation, where meaning is negotiated through a recursive cycle of computational generation and human refinement. Unlike human-made drawings, which evolve through embodied engagement, AI-generated representations are probabilistic snapshots that require linguistic fine-tuning rather than a mandatory manual revision. This distinction positions AI-mediated *èkphrasis* as an exploratory mode of representation, highlighting that AI prompting is

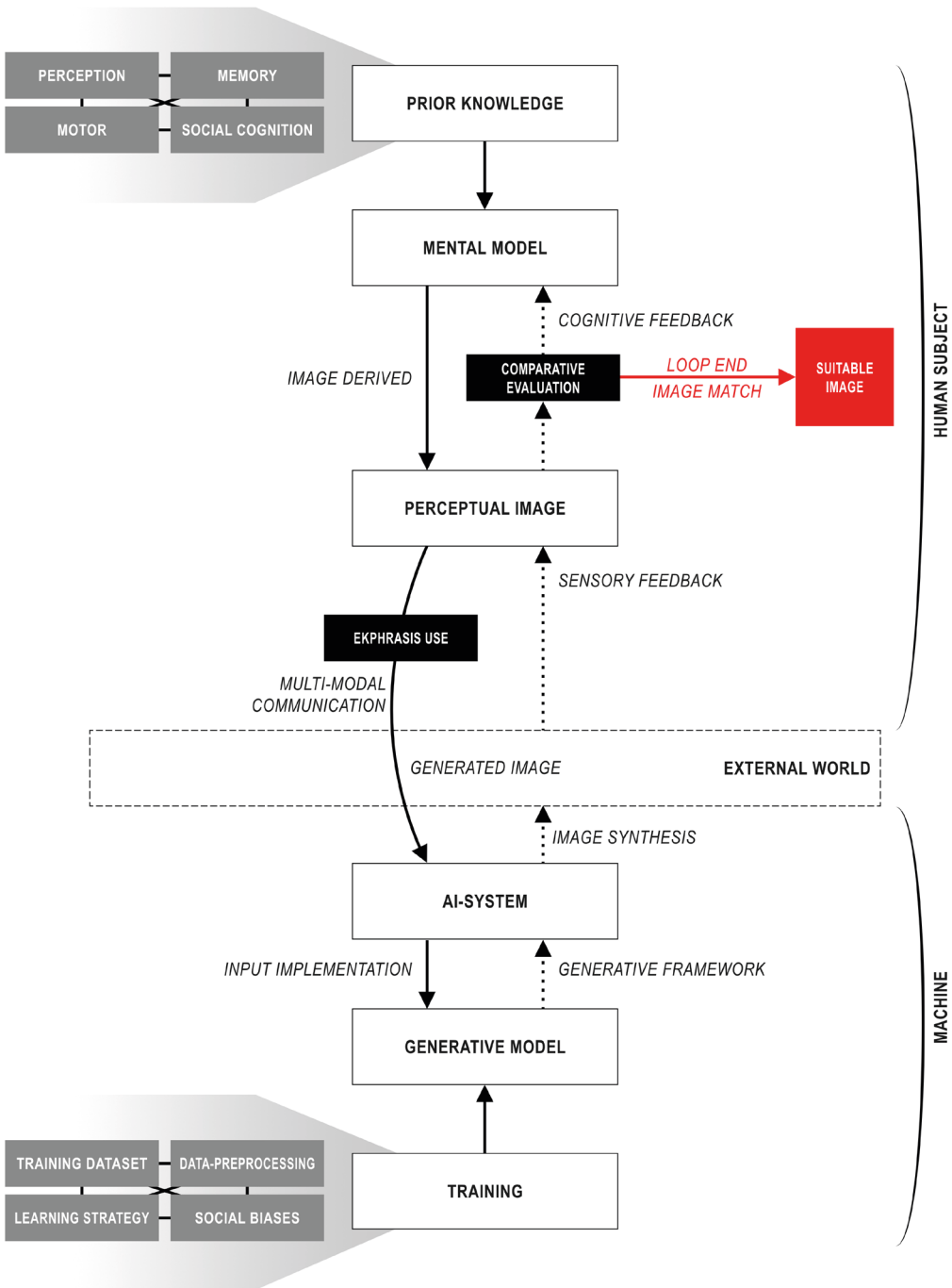

Fig. 5. Conceptual representation of AI-driven *èkphrasis*, illustrating the interplay between human intent, linguistic input, and probabilistic visual output.

more about navigating a flexible, associative meaning space than issuing prescriptive instructions (fig. 5).

Towards a new ekphrastic paradigm: from descriptive language to evocative keywords

A key shift in AI-assisted *èkphrasis* is the transition from rich, syntactically complex descriptions to concise, referential prompt engineering. Traditional ekphrasis often employs extended metaphor, detailed spatial descriptions, and affective resonance to guide the reader's mental reconstruction of an artwork. In contrast, AI-assisted *èkphrasis* prioritizes brevity and associative strength, using keywords, references to artistic movements, and compact stylistic cues aligned with the model's training data [Scorzin 2024].
This shift is particularly evident in the mechanics of prompting within widely used generative models such as *DALL·E*, *Midjourney*, and *Stable Diffusion*, where users quickly discover that long, complex sentences –akin to traditional literary ekphrasis– often lead to semantic noise, dilution of stylistic intent, or unexpected compositional errors [Takale *et al.* 2024]. Instead, these models respond most effectively to highly condensed, semantically loaded terms – what might be termed ekphrastic triggers– which efficiently activate specific visual domains within the model's latent space.
For instance, rather than describing 'a highly detailed urban scene with a melancholic, cinematic atmosphere and a focus on strong chiaroscuro contrasts', a prompter might achieve better

Fig. 6. Comparison between evocative, concise prompts and detailed, descriptive prompts in AI image generation, showing how brevity can sometimes yield superior results.

results simply by invoking 'Edward Hopper-inspired noir cityscape', a phrase that condenses both aesthetic intent and interpretative flexibility into a single reference [Schröter 2024]. This transformation indicates that effective AI-generated ekphrasis focuses less on describing an image and more on strategically evoking concepts aligned with pre-trained model biases (fig. 6). This phenomenon highlights a core principle of current applications for AI-assisted *èkphrasis*: evocation, rather than exhaustive description, enhances generative accuracy and aesthetic coherence. The closer an ekphrastic phrase aligns with a well-established visual archetype in the model's dataset, the more effectively and predictably the system generates a corresponding image. In contrast, overly specific or idiosyncratic phrasing may disrupt the model's interpretative focus or result in stylistic inconsistency [Mageed, Nazir 2025]. This dynamic challenges the traditional assumption that greater descriptive detail necessarily results in higher visual fidelity. Instead, in AI-mediated *èkphrasis*, abstraction and conciseness often yield richer, more convincing interpretative outputs.

A reconfiguration of ekphrastic methodology: Smart Guessing and Digital Synesthesia

This shift has practical implications for human-AI interaction, emphasizing the need for smart guessing, where users develop an intuitive understanding of how AI links language to visual patterns, refining prompts accordingly. Unlike traditional artistic description, which aims to fix meaning, AI-assisted prompting requires the prompter to anticipate, experiment, and adjust linguistic cues, strategically compressing complex visual intentions into concise, semantically rich input [Herman, Hutka 2019].
Moreover, one of the most intriguing developments in AI-driven *èkphrasis* is the rise of multimodal AI systems, which are not limited to text-to-image transformations but integrate multiple sensory inputs into a unified interpretative process [Bolwin 2024; Mageed, Nazir 2025].
This computational cross-modal integration mirrors human synesthesia, where one sensory stimulus triggers another. While biological synesthesia arises from neural cross-activation, AI uses vector embeddings to encode text, images, and other modalities into a shared space, enabling meaningful yet unexpected interpretations. This form of 'digital synesthesia' is particularly relevant to ekphrasis, as poetic texts have long used cross-sensory associations to create evocative descriptions of artworks. Just as a poet might describe a painting in musical terms or a sculpture through tactile sensations, multimodal AI models synthesize sensory dimensions from layers of structured data, generating cohesive outputs across multiple representational formats.

Expanding *èkphrasis* through AI: from evocative language to computational knowledge integration

The evolution of AI-assisted *èkphrasis* is not confined to the realm of purely aesthetic or interpretative image generation. Beyond functioning as a tool for evocative visual transformation, AI is increasingly being integrated into domains where linguistic prompts not only describe but also structure complex, data-driven, and technically informed outputs [Sourek 2024]. This shift is particularly visible in fields such as architectural design, computational fabrication, and AI-mediated parametric modeling, where textual input can be used not just to evoke stylistic and compositional frameworks but also to embed material, spatial, and engineering constraints within the generated results [Nawaz, Rasool 2025].
In such cases, ekphrasis ceases to be merely an interpretative bridge between text and image and becomes a multi-layered interface between textual input, encoded knowledge, and executable logic (table 3).
A key distinction between AI-driven aesthetic generation and AI-assisted technical execution lies in the nature of the underlying models and their relationship with structured data. While generative models like *Midjourney* and *DALL·E* respond primarily to associative language triggers within a latent space of stylistic and compositional patterns, other AI systems –such as those integrated into BIM (Building Information Modeling), AI-assisted procedural design engines, or generative code-based platforms– rely on explicitly structured, rule-based constraints that allow for technically robust outputs [Nisar 2024].

MODE OF AI-DRIVEN EKPHRASIS	INTERPRETATION MECHANISM	DEGREE OF CONSTRAINT	APPLICATION CONTEXT
Evocative, Freeform Ekphrasis (e.g., Midjourney, Stable Diffusion)	*Latent-space interpolation based on stylistic cues*	*Low (open-ended generation)*	*Artistic creation, conceptual visualization*
Structured, Knowledge-Based Ekphrasis (e.g., AI-assisted parametric design, BIM-integrated AI)	*Text-to-rule translation; generative logic integrates technical constraints*	*High (adheres to domain-specific rules)*	*Architectural design, computational modelling, engineering simulation*

Table 3. *Èkphrasis* for free artistic creation *vs.* AI-assisted *èkphrasis* for real-world, knowledge-based applications in architecture and design.

This creates a continuum between freeform generative *èkphrasis*, in which the outcome remains open-ended and probabilistic, and structured AI-driven ekphrasis, where outputs must conform to functional, regulatory, or material-specific criteria.
This transition means that AI does not merely reinterpret ekphrastic input in a stylistic manner but may contextualize it within embedded knowledge frameworks, such as:
- architectural grammars and spatial typologies:AI can integrate established design languages, procedural typologies, and formal constraints, ensuring coherence with traditional and contemporary architectural vocabularies;
- material constraints and performance-based optimizations: AI can factor in structural efficiency, material sustainability, and fabrication feasibility, transforming a textual description into an optimized generative model [Nisar 2024];
- regulatory standards and generative design principles: AI can embed zoning laws, energy efficiency parameters, and human-centered ergonomic factors into the generated outcomes.
In technically integrated AI systems, the prompter takes on the role of both guide and designer, encoding not just intent but an operational framework. This is evident in AI-augmented architectural design, such as *Studio Tim Fu*, where AI aids in creating material-efficient, structurally sound, and fabrication-ready forms (*Tim Fu Studio*). Here, textual input is not just suggestive but directive, influencing not only style and form but also performance, sustainability, and constructability. For *èkphrasis*, this means that descriptive language in AI-driven design goes beyond interpretation into execution. In traditional *èkphrasis*, language generates an imagined visual counterpart, but in AI-driven workflows, it actively shapes the generative process. This redefines *èkphrasis* as both an interpretative tool and a design methodology.
Thus, in its most advanced form, AI-assisted *èkphrasis* extends beyond the act of image evocation and into the realm of design execution, where the role of language is no longer merely expressive but functionally instructive. Whether in artistic, architectural, or engineering applications, AI's ability to synthesize evocative input with structured knowledge points toward a new paradigm of multimodal ekphrasis, where the verbal, the visual, the sensorial at large, and the computational become interwoven into a unified creative process. This evolution aligns with broader multimodal trends in AI research, where text, image, and domain-specific knowledge are increasingly interconnected [Latha 2025]. This transformation brings new challenges regarding interpretative ambiguity and the prompter's responsibility as a computational decision-maker. When an AI model expands or optimizes a concept beyond the designer's initial assumptions, the prompter becomes more than a recipient of machine-generated results; they are a curator of computational reasoning, responsible for validating, refining, and ultimately assuming authorship of AI-driven outputs. This process mirrors trends in AI-assisted art and generative architecture, where the lines between human intent, machine optimization, and emergent design outcomes are increasingly blurred.

Conclusion

The growing role of AI in text-to-image generation suggests that *èkphrasis* is evolving beyond a descriptive literary device. AI-driven ekphrasis moves beyond simply verbalizing static artworks, becoming a generative methodology where text actively co-produces the image (Bolwin,

2024). This challenges traditional notions of authorship, artistic agency, and interpretation. Unlike traditional *èkphrasis*, which relies on language to evoke imagery, AI-generated *èkphrasis* introduces a bidirectional feedback loop between text and image, requiring the prompter to experiment, refine, and adapt their input [Mageed, Nazir 2025]. In this way, AI-mediated *èkphrasis* aligns with earlier interactive, conceptual, and procedural art movements, where human intent is translated into structured instructions, but the final outcome remains variable.
This transformation creates both new possibilities and challenges:
- expanded expressive potential: AI-assisted *èkphrasis* allows for new hybrid artistic practices, where textual and visual elements continuously influence one another [Mageed, Nazir 2025];
- loss of direct artistic control: AI-generated images are not fully determined by the prompter, raising concerns about algorithmic opacity and bias [Bolwin 2024];
- the shift toward editorial authorship: unlike traditional artistic creation, AI-driven ekphrasis places authorship not in execution, but in selection and refinement, positioning the prompter as a curator rather than a direct creator [Schröter 2024].
Thus, AI-driven *èkphrasis* is no longer about translating words into images but about mapping conceptual associations across multiple sensory dimensions, a shift that repositions *èkphrasis* from a purely linguistic practice to a multimodal, generative framework.

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Authors
Lorenzo Ceccon, Politecnico di Milano, lorenzo.ceccon@polimi.it
Matteo Cavaglià, Politecnico di Milano, matteo.cavaglia@polimi.it

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