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The Drawing is dead, Long live the Drawing! The Role of Architectural Drawing in the Digital Ecosystem: Continuity, Control, and Transformations across Generative AI, CAD, BIM, and XR

The contribution proposes a critical reflection on the role of architectural drawing within the contemporary digital ecosystem, shaped by the integration of CAD, three-dimensional modeling, BIM, XR environments, and generative artificial intelligence (AI) systems.
The paradox “The Drawing is dead, Long live the Drawing!” does not announce the end of drawing; rather, it highlights the Drawing’s transformation from a productive practice into a cognitive device for controlling and verifying the project.
The paper frames the evolution of AI by distinguishing between Artificial Narrow Intelligence and Artificial General Intelligence, and analyzes generative models based on machine learning and deep learning, emphasizing their probabilistic nature and the gap between visual plausibility and semantic understanding.
In this context, the designer is no longer only the author of the sign, but also responsible for the conditions that guide image generation. Through a comparative analysis of traditional tools and AI applications, structured around the main phases of representation, the contribution shows that these technologies are particularly effective in the exploratory and communicative stages, enabling the rapid production of alternatives and visualizations.
However, limitations persist in terms of geometric control and design coherence, highlighting the distinction between a plausible image and a technically and semantically coherent design.
The contribution concludes that AI does not replace drawing but redefines its functions, reaffirming its role as a critical practice that mediates among conception, representation, and the project’s cultural responsibility.

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Keywords:
Architectural Drawing; Architectural Education; Surveying; Design Process; Representation; Generative Artificial Intelligence

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INTRODUCTION

In recent years, artificial intelligence (AI) has emerged as one of the main drivers of transformation in contemporary cognitive and productive systems.
The thesis of this contribution is that AI does not replace architectural drawing. Still, it shifts its center of gravity from image production to the critical control of generative processes.
Its impact extends beyond the technological dimension to encompass the processes of knowledge production, organization, and transmission (Ai, 2018; Zhai et al., 2021; Siau & Wang, 2020; Singh & Gill, 2023; Cui et al., 2025).
The transformation of representational tools calls for reflection on how graphic practices can redefine the relationship among observation, interpretation, and project construction.
From this perspective, the introduction of new technologies does not constitute a mere operational substitution, but rather a redefinition of the cognitive processes underlying representation. As highlighted in disciplinary debates, drawing remains an intentional act of thought, not merely the product of a tool (Mingucci, 2017).
It can be understood as a hermeneutic device capable of interpreting built reality and returning a critical representation of it, rooted in the disciplinary tradition of architecture.
Generative AI, however, introduces a discontinuity in the relationship between conception, representation, and image production (Banh & Strobel, 2023; Lv, 2023).
Systems based on machine learning and deep learning can now generate complex visual configurations from linguistic or visual inputs, simulating plausible design outcomes (Shinde & Shah, 2018; Taye, 2023).
This entails a shift in the relationship between designer and tool: whereas in traditional drawing the designer directly formulates hypotheses through the sign, in AI applications the operator tends to delegate image generation.
Current applications fall within the domain of Artificial Narrow Intelligence (ANI), systems that operate through statistical correlations learned from data (Kuusi & Heinonen, 2022; Babu & Banana, 2024).
These models produce visually plausible results, but lack genuine semantic understanding (Goodfellow et al., 2016; Marcus, 2018; Bender et al., 2021; Floridi & Chiriatti, 2020).
This raises a central issue: the relationship between design control and the automation of representation. If drawing loses its function as a means of verifying design thinking, its educational and disciplinary value risks being compromised.
The introduction of AI, therefore, requires critical reflection on how design knowledge is constructed and transmitted (Mitchell, 2019; Floridi, 2019). Every innovation in representation techniques—from perspective to CAD, BIM, and XR systems—has entailed a redefinition of design methods and responsibilities (Banfi, 2025).
Within this framework, the paradox **"The Drawing is dead, Long live the Drawing!"** highlights the potential replacement of certain operational skills, but not the designer's critical responsibility (Fig.1).
Drawing continues to take shape as a practice of knowledge and project control, as well as a language of communication between the designer and AI-based systems.

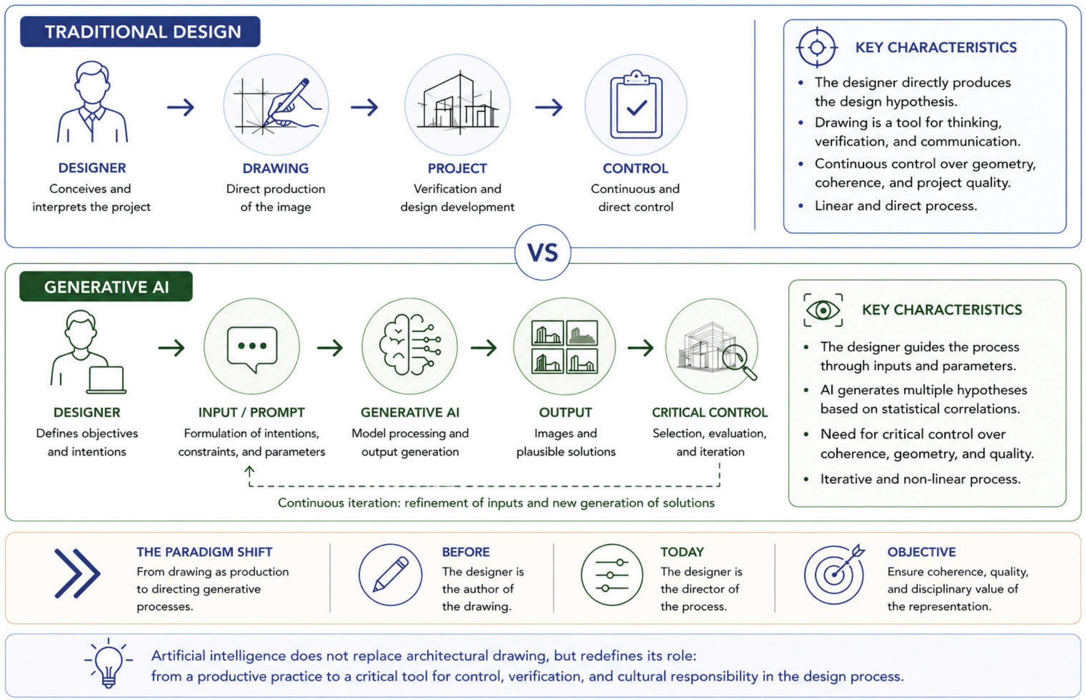

Fig. 1 - Comparative diagram between traditional drawing and AI-based processes in architectural representation. The diagram highlights the shift from the direct production of the image to the critical control of generative processes, redefining the designer's role from author of the sign to director of the process.

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The future of graphic sciences calls for an integrated reflection across research, education, and design practice, capable of identifying new competencies and redefining existing ones.
Within this perspective, the present contribution aims to define and analyze an integrated model in which drawing and AI operate in complementary ways, as summarized in the proposed diagram, highlighting how the designer's critical control and the generative and analytical capabilities of AI systems can interact within a single design process (Fig. 2).
The objective is not to oppose traditional approaches and emerging technologies, but to understand how such systems can be consciously integrated, enhancing, on the one hand, the speed and exploratory capacity of AI and, on the other, the role of drawing as a device for verification, interpretation, and construction of the project. Within this framework, the proposed model seeks to offer an interpretative key for understanding ongoing transformations, orienting architectural representation toward hybrid design workflows in which process automation and the designer's critical responsibility emerge as interdependent elements. The aim is not to contrast drawing with emerging technologies, but to understand their integration within a methodological framework that preserves the critical value of representation.

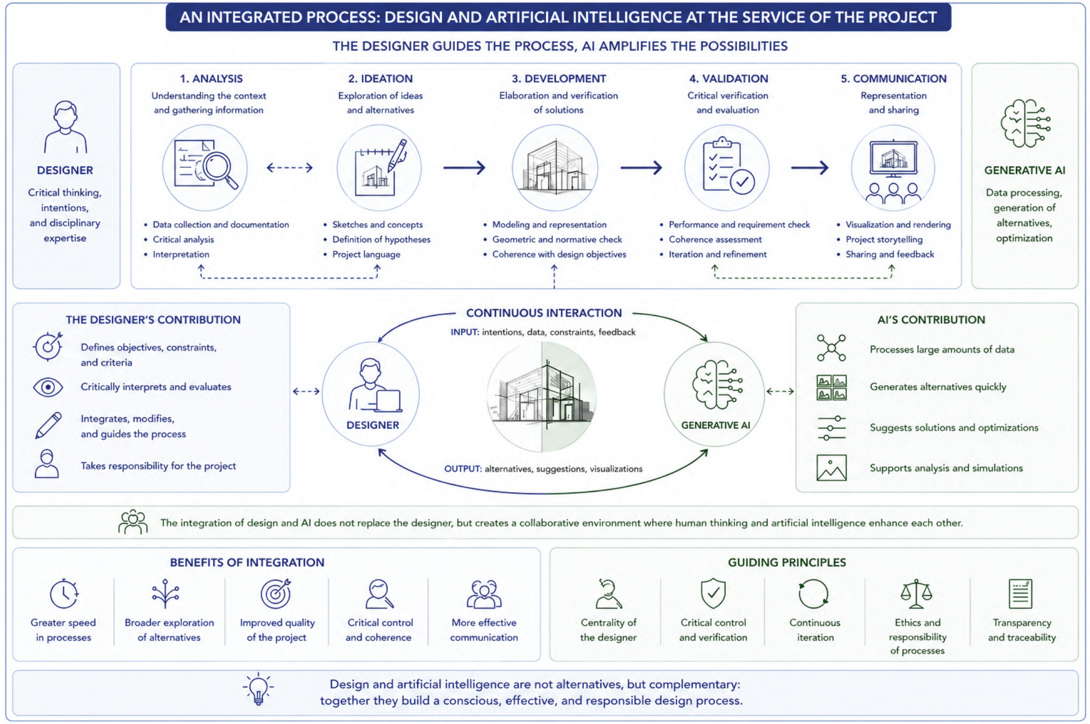

Fig. 2 - Diagram of the integrated process between architectural drawing and AI. The diagram represents the continuous interaction between the designer and AI systems across the stages of the design process, highlighting the complementarity between human critical control and AI's generative and analytical capabilities.

AI AND ARCHITECTURAL REPRESENTATION: THEORETICAL AND APPLIED CONTEXT

In contemporary debate, AI is defined as the set of computational techniques aimed at building systems capable of simulating human cognitive functions such as pattern recognition, learning from data, and operational inference (Nilsson, 2009; Russell & Norvig, 2021). Since early postwar reflections—including the Turing test—the discourse has distinguished between models oriented toward simulating cognitive processes and systems designed to act rationally in complex environments (Turing, 2007; McCarthy et al., 2006).
In the current landscape, the distinction between Artificial Narrow Intelligence (ANI) and Artificial General Intelligence (AGI) is well established: the former refers to specialized systems based on the analysis of large datasets, while the latter represents a theoretical form of intelligence comparable to human cognition (Bostrom, 2014; Goertzel & Pennachin, 2007).
Today's applications belong almost exclusively to the first category and rely on machine learning and deep learning techniques, in which learning arises from training neural networks to identify correlations in data (Murphy, 2012; LeCun et al., 2015; Domingos, 2015).
In this process, the quality and structure of data are decisive for model performance.
Among the most relevant application fields is computer vision, which enables the analysis of visual content through classification, segmentation, and recognition tasks (Szeliski, 2022; Krizhevsky et al., 2012). Alongside these technologies, generative models—such as GANs and diffusion models—can produce new visual configurations from linguistic or iconic inputs (Goodfellow et al., 2014; Ho et al., 2020).
This alters the relationship between image and design. Whereas in traditional practices the ima-

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ge resulted from an interpretative process conducted by the designer, in generative systems it may emerge from statistical processing.
In this scenario, the designer is no longer the sole author of the image but becomes responsible for the conditions that guide its generation: selecting data, defining parameters, and interpreting outcomes. A transfer of competencies thus takes place toward tools that amplify speed and precision, redefining the designer's role as a director of the process. This transformation is particularly evident in architectural representation, where recent experiments integrate AI systems into design workflows. Among the most notable cases, the collaboration between Zaha Hadid Architects and NVIDIA has explored the use of generative models trained on the studio's visual archives to produce configurations consistent with its design language. The integration of the NVIDIA Omniverse platform with environments such as Maya and Unreal Engine has also enabled the development of collaborative environments for real-time model and simulation management. Similarly, the Vitras.io software, developed by Cove Architecture, has demonstrated how AI-assisted design systems can optimize BIM models by integrating environmental parameters and regulatory constraints, reducing time and costs. However, these experiences also reveal significant limitations: while the outputs are often visually effective, they do not always address the project's constructional and regulatory complexity. This leads to a fundamental distinction between visual plausibility and design coherence, which is central to the critical evaluation of such tools. From a disciplinary perspective, it is therefore necessary to distinguish between the image as a tool of knowledge and the image as a generated product.
In the first case, drawing retains its function as a cognitive control device; in the second, it risks being reduced to a purely visual simulation devoid of interpretation. The spread of AI does not, therefore, imply the marginalization of drawing, but rather reinforces its role as a critical device for constructing and controlling generative processes.

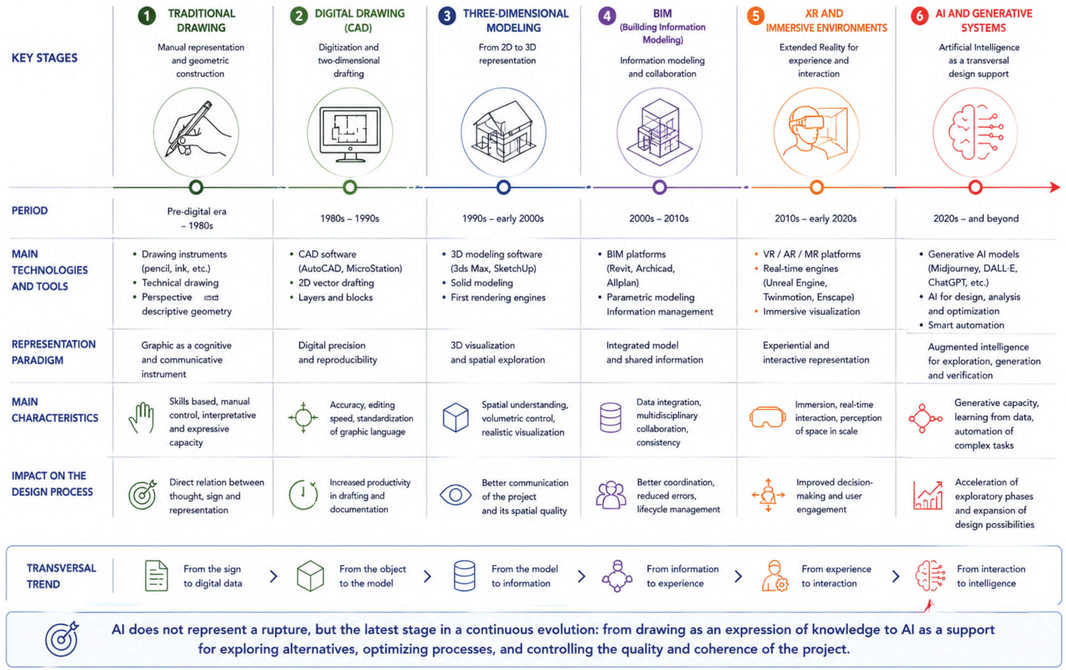

Fig. 3 - Evolution of architectural representation tools from traditional drawing to AI-based systems. The diagram highlights the progressive transformation from manual representation to digital modeling (CAD, BIM), immersive environments (XR), and the integration of AI as a transversal layer supporting design processes.

The key issue is not AI's ability to produce images, but the possibility of preserving, within drawing, the functions of verification, selection, and design responsibility.
Within this framework, the evolution of architectural representation can be interpreted as a continuous transformation of tools, methods, and cognitive processes, from manual drawing to contemporary AI-based systems, as illustrated in the following timeline (Fig. 3).
The design process can be interpreted as a continuous flow of information, in which AI operates as a generative and analytical layer. At the same time, the designer retains a central role in control, interpretation, and validation (Fig. 4).

DIGITAL ECOSYSTEM OF ARCHITECTURAL REPRESENTATION

Understanding the operational modalities of these systems is a fundamental step in assessing their use. They are not based on a single tool, but rather on a complex set of platforms and applications that intervene at different stages of the design process.
In recent years, the spread of deep learning has fostered the development of technologies capable of generating images as well as analyzing and optimizing design models. These tools are part of a progressive evolution of architectural representation: from CAD systems, which digitized traditio-

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nal drawing, to BIM models, which introduced an informational and parametric dimension to design by integrating geometric, constructional, and performance data. AI-based platforms now represent a further layer of this evolution, introducing automation into the production and processing of visual configurations.
The analysis aims to understand the qualitative and operational differences that emerge when such tools are applied to realistic design scenarios. The focus is not only on the performance of individual software packages, but also on their impact on the designer's workflow and on the construction of architectural imagery.
The applications considered were selected based on three criteria: coherence with the research objectives, accessibility, and integration into design workflows.
Not all tested systems fully met these conditions: some, despite promising advanced functionality, proved difficult to access or too complex to use without specific technical expertise; others revealed critical issues in interface design or integration with existing tools.
However, these limitations also constitute meaningful elements of the research framework, as they help clarify the operational complexity of a field still being defined. Without promoting specific platforms, it is possible to critically compare AI tools with traditional digital methods by defining an operational environment structured into different functional categories:
CAD systems for two-dimensional drafting, such as Autodesk AutoCAD, used for the production of technical drawings and the digital translation of traditional graphic techniques; Three-dimensional modeling tools, such as Rhinoceros, Blender, and SketchUp, used for form definition and the management of complex geometries intended for visualization and simulation;
BIM platforms, such as Autodesk Revit and Graphisoft Archicad, which integrate an informational dimension into the model, including constructional, performance, and energy data;
XR (Extended Reality) environments, such as Twinmotion, Unreal Engine, Unity, and MetaHuman Creator, which enable immersive experiences and real-time visualization of the design. Taken together, these tools show how contemporary architectural design develops through a plurality of operational environments: from two-dimensional drawing to three-dimensional modeling, from BIM to HBIM semantic representations for built heritage (Rossi et al., 2026), and immersive XR environments (Banfi, 2026).
Within this ecosystem, AI applications are inserted, operating transversally across different platforms. AI is therefore not a simple additional tool, but a technological layer that traverses and connects existing environments, intervening in image generation, model optimization, and the analysis of design information.

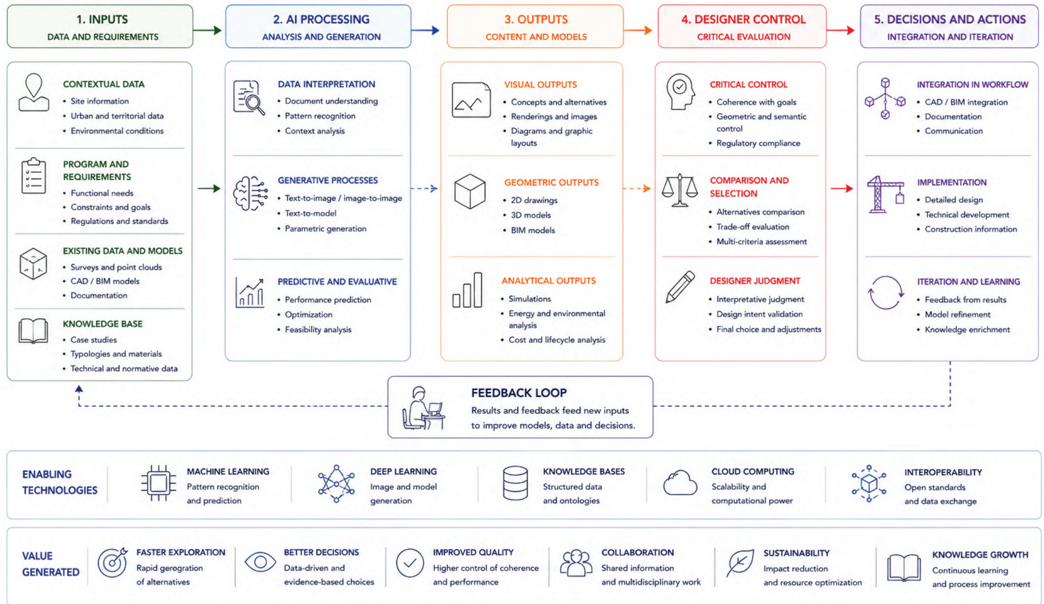

Fig. 4 - Information flow map in AI-augmented architectural design. The diagram illustrates how AI processes transform data into design outputs, highlighting the designer's central role in the critical evaluation, selection, and integration of generated results within an iterative workflow.

Understanding these relationships is essential for evaluating their role within architectural representation processes.

AI APPLICATIONS IN ARCHITECTURAL REPRESENTATION

To understand the role of AI in architectural representation processes, it is useful to distinguish among different types of applications based on their operational functions.
AI does not take the form of a single tool, but rather a set of technologies that intervene at different moments of the design process, interacting with established digital environments such as

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CAD systems, 3D modeling tools, BIM platforms, and XR environments. Within this framework, AI applications can be grouped into three functional categories: generative AI, operational and optimization AI, and cognitive AI.
This classification helps highlight the distinct roles these systems play across the phases of ideation, development, and communication in the design process.
The first category includes generative AI systems, i.e., tools capable of producing visual, spatial, or three-dimensional configurations from textual or geometric inputs. This is one of the most dynamic areas of AI applied to design, as it enables the rapid exploration of compositional alternatives and design scenarios. This category includes platforms such as ArchitectGPT, AlcasaDesign, ArchSynth, Rendair.ai, and ReRender.ai, as well as 3D generation tools such as Meshy.ai, Tripo, and MeshMastery, and widely used solutions such as Planner 5D and LookX. It also includes applications widely used for image production, such as Midjourney, DALL·E, and Adobe Firefly, as well as tools for urban and parametric design such as Archistar, MyArchitectAI, and TestFit. In all these cases, AI directly influences the generation of images or geometry, expanding the space of design alternatives within reduced timeframes.
The second category includes operational AI tools, which do not directly generate images but support the design process through analysis, automation, and optimization.
This group includes solutions integrated into major BIM and CAD software: Autodesk develops AI tools for platforms such as Revit and Autodesk Forma; Graphisoft integrates intelligent features into Archicad; and ACCA Software uses AI systems for energy analysis and regulatory compliance checks. Additional tools such as Snaptrude, Swapp, and Hypar automate BIM model generation and documentation production.
In the field of visualization, real-time engines and rendering tools such as Enscape, Twinmotion, Chaos Vantage, D5 Render, and Lumion also integrate AI functionalities to optimize and accelerate workflows. These tools do not directly produce design configurations but improve the quality, consistency, and speed of the workflow.

AI CATEGORY	FUNCTION	TOOLS (EXAMPLES)	OUTPUT	INTEROPERABILITY
COGNITIVE AI	Analysis and konwledge support	ChatGPT, Claude, SciSpace Copilot	Technical content (.txt, .docx, .pdf)	CAD · BIM · 3D
COGNITIVE AI (DOCUMENT ANALYSIS)	Document analysis	LightPDF AI	PDF summaries	BIM · CAD workflows
2D GENERATIVE AI	Concept generation and images	Midjourney, DALL-E, Adobe Firefly, ArchitectGPT, Maket.ai	Images (.png, .jpg)	CAD · BIM
ARCHITECTURAL GENERATIVE AI	Interior design and layout generation	AlcasaDesign, Planner 5D	2D / 3D models (.obj, .fbx)	SketchUp · Blender
3D GENERATIVE AI	3D model generation	Meshy.ai, Tripo, Luma AI	3D models (.obj, .fbx, .glb)	Rhino · Unreal Engine
AI FOR RENDERING	Image rendering	Rendair.ai, ReRender.ai, LookX, Veras	Render images (.png, .jpg)	Revit · SketchUp
BIM AI	Design automation	Revit AI, Archicad AI, Hypar	BIM models (.rvt, .ifx)	Integrated BIM environments
AI FOR ANALYSIS	Performance analysis	ACCA AI, Cove.tool	Simulations	BIM
URBAN AI	Masterplanning	TestFit, Archistar	Studies (.pdf)	BIM · GIS
PARAMETRIC AI	Algorithmic modeling	Grasshopper, Dynamo	Scripts and models	CAD · BIM
DIGITAL TWIN	Real-time simulation	Omniverse, iTwin	Digital environments	BIM · XR
SCAN-TO-BIM	AI-based surveying	OpenSpace, Buildots	Point clouds	BIM
REAL-TIME RENDERING	Visualization	Enscape, Twinmotion, Lumion	Videos and scenes	CAD · BIM
XR (EXTENDED REALITY)	Immersive simulation	Unreal Engine, Unity	VR/AR environments	XR · BIM
AI SUPPORT (TRANSVERSAL)	Assistance and scripting	ChatGPT, Claude	Texts, scripts, decision support	Cross-platform

INTEGRATION IN THE WORKFLOW: CONCEPT & RESEARCH → MODEL & DEVELOPMENT → ANALYSIS & OPTIMIZATION → VISUALIZATION & COMMUNICATION → XR & IMMERSIVE EXPERIENCES → DOCUMENTATION & MANAGEMENT

Table 1- Classification of AI tools in architectural representation, organized by functional categories (generative, operational, and cognitive AI), functions, software, and areas of interoperability, with reference to the different stages of the design workflow, from ideation to information management and project visualization.

The third category includes cognitive AI tools, used for the analysis, synthesis, and interpretation of technical and scientific information.
This includes large language models such as OpenAI GPT (ChatGPT) and Claude, as well as platforms like LightPDF AI and SciSpace Copilot for document extraction and summarization. While they do not directly intervene in image construction, these systems support the design process in research and information management phases.
Together, these categories show how AI operates transversally across digital environments in architectural design.
Generative tools interact with 3D modeling and XR environments; operational tools are integrated into BIM systems; and cognitive tools support the entire information workflow.
Table 1 highlights this structure, while Figure 5 illustrates how these tools integrate across different phases of the workflow: generative tools for visualization and immersive content production; operational tools for analysis and optimization; and cognitive tools for information management.
The result is a technological ecosystem in which AI does not replace existing tools but is embedded within them, expanding their potential and modifying the way designers construct and interpret architectural images.

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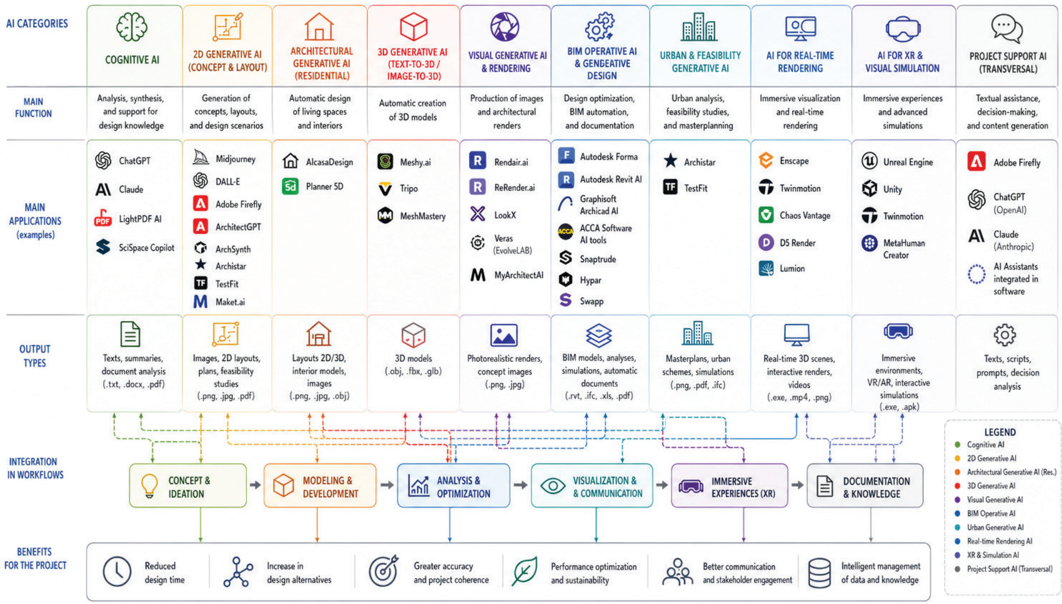

Fig. 5 - Diagram of the AI ecosystem in architectural representation, illustrating the main categories (cognitive AI, 2D/3D generative AI, BIM, rendering, simulation, etc.), the most widely used applications, the types of outputs produced, and their integration into the different stages of the design workflow, from concept to documentation, highlighting benefits in terms of efficiency, quality, and project communication.

The experimental analysis presented focuses on a selected set of these applications to evaluate their integration into workflows and their operational implications relative to traditional methodologies.

METHODOLOGICAL FRAMEWORK AND ANALYTICAL CRITERIA

The comparison between traditional representation tools and AI-based applications requires a methodological framework that enables substantially different operational processes to be compared.
The proposed experimentation aims to assess how generative systems and AI applications affect the production of architectural images, with particular attention to the stages of design construction, interpretation, and communication.
The research adopted a comparative and exploratory approach, based on the analysis of multiple design scenarios that are representative of common architectural representation tasks.
Rather than focusing on a single case study, the experimentation involved a set of design configurations that differed in scale, geometric complexity, and representational objectives, including conceptual design, architectural modeling, and visualization activities.
This approach was intended to identify recurring operational patterns and limitations that could be observed independently from specific project characteristics. The experimentation included the use of both traditional digital tools (CAD, BIM, 3D modeling, rendering, and XR platforms) and selected AI applications across the previously defined categories of generative, operational, and cognitive AI.
The selected tools were chosen according to three criteria: relevance to architectural representation processes, accessibility for professional and educational use, and effective integration within existing design workflows.
The operational procedures were tested by users with different levels of expertise, including designers experienced in digital representation and non-specialist users with limited technical backgrounds. This choice made it possible to evaluate not only the tools' performance but also their accessibility, learning requirements, and dependence on user expertise.
The comparison was conducted across both professional and educational contexts, where AI systems are increasingly adopted as support tools for design and representation activities.
It should be emphasized that the experimentation was conceived as a qualitative comparative investigation rather than a quantitative performance benchmark. The aim was not to measure the absolute efficiency of individual software applications or to generate statistically representative findings; instead, it sought to identify recurring operational patterns, critical limitations, and potential forms of complementarity between conventional representation methods and AI-assisted workflows.
To ensure consistency and comparability across the different case studies, the experimentation was organized into four operational phases common to all tested workflows:
analysis of preliminary design documentation;
two-dimensional graphic restitution of floor plans;
construction of digital three-dimensional models;
production of perspective visualizations, renderings, and immersive outputs.
For each phase, traditional and AI-assisted procedures were evaluated using a common set of analytical criteria.
The assessment focused on both operational performance and design implications, considering:
- hardware performance;

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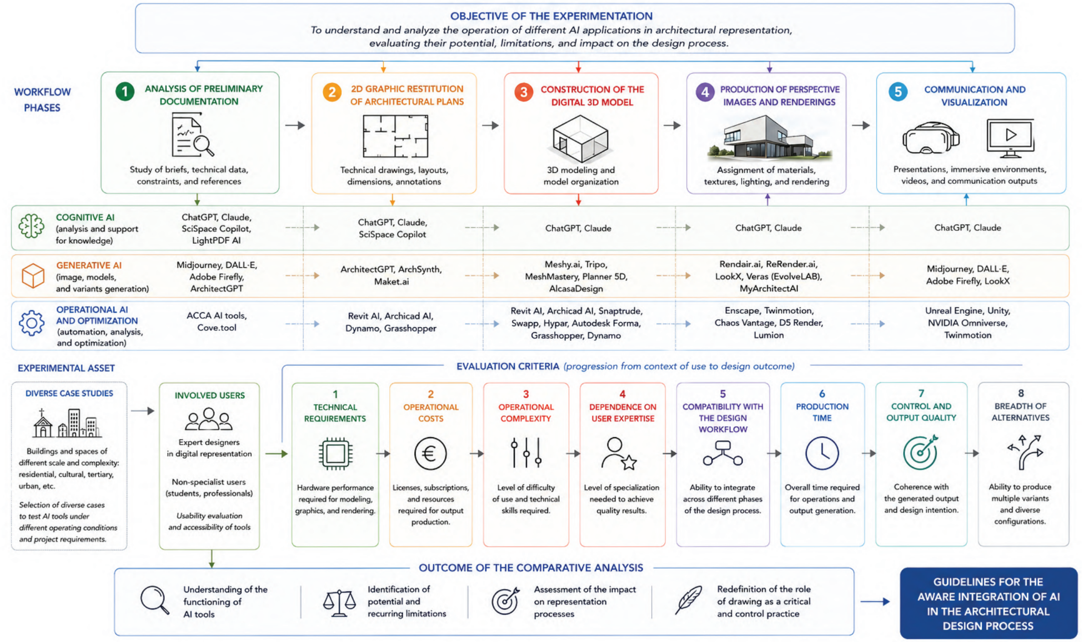

Fig. 6 - Methodological framework for the comparative analysis of AI tools in architectural representation, integrating design workflow stages, AI application categories, and the evaluation criteria adopted in the study.

- operational costs (licenses and computational resources);
- operational complexity (difficulty of use);
- dependence on user expertise;
- compatibility with the design workflow;
- production time;
- degree of geometric and semantic control over the output;
- capacity to generate design alternatives.

The collected observations were analyzed using a comparative qualitative framework, supported by repeated testing across different scenarios and user profiles. Rather than measuring absolute performance values, the objective was to identify recurring tendencies, advantages, and critical issues emerging from the interaction between designers and AI systems. This approach allows the discussion to focus on the implications of AI for architectural representation, not only as a technological innovation but also as a transformation of the cognitive and operational role traditionally associated with drawing.

Taken together, these parameters constitute the methodological basis for the comparative analysis presented in the following sections, which aims to evaluate the role and potential of AI applications in architectural representation (Fig. 6).

From this perspective, the analysis is not limited to assessing technical performance but also investigates how the introduction of AI affects the role of drawing in the design process, understood not only as a means of representation but also as a cognitive device through which the designer constructs, verifies, and interprets architectural space.

It should be clarified that the experimentation was conceived as a qualitative comparative assessment rather than as a quantitative performance benchmark. The objective was not to measure the absolute efficiency of individual software packages, but to identify recurring operational tendencies, critical thresholds, and forms of complementarity between traditional representation tools and AI-assisted procedures. For this reason, the evaluation focuses on the relationship between workflow, control, output quality, and design responsibility.

RESULTS OF THE EXPERIMENTATION AND COMPARATIVE ANALYSIS

The comparative experimentation was conducted across multiple architectural representation tasks and different categories of AI applications. The objective was not to determine absolute performance values for individual software packages, but rather to identify recurring operational tendencies emerging from the interaction between traditional workflows and AI-assisted procedures. The observations collected during the tests were therefore synthesized within a comparative framework based on the evaluation criteria defined in Section 4, thereby enabling the identification of strengths, limitations, and areas of complementarity among the different approaches.

The experimental phase aimed to critically analyze the behavior of traditional representation tools and AI–based applications in the production of architectural images and digital models. Consistent with the methodological framework described in the previous section, the experimentation was conducted across heterogeneous application scenarios to identify recurring operational dynamics independent of specific design configurations.

The analysis was structured into four operational stages corresponding to the main phases of the representation process: analysis of techni-

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cal documentation, two-dimensional drafting, three-dimensional modeling, and production of final visualizations (images, videos, and XR environments).
The first stage concerned the analysis of technical documentation. In this area, the comparison highlighted that traditional tools require interpretative work by the designer, whereas cognitive AI systems enable automated extraction and synthesis of information in significantly reduced timeframes. These tools prove particularly effective in early research phases, although they require critical oversight to verify the reliability and relevance of generated content.
The second stage concerned two-dimensional drafting. Traditional methods using CAD tools provide direct control over geometry and spatial definition. Generative tools, by contrast, enable the rapid production of layout configurations from textual or parametric inputs, significantly expanding the number of design alternatives to explore. However, critical limitations emerge in handling complex or non-standard configurations, revealing a gap between automated generation and geometric control of the design.
The third stage concerned three-dimensional modeling. In the traditional approach, the model is constructed through a progressive and controlled process that ensures coherence between geometry and design intent. AI-based tools, by contrast, yield heterogeneous results: while they enable the rapid generation of three-dimensional models, they often produce simplified outputs that are difficult to modify. This highlights how automated modeling remains limited in its ability to manage spatial complexity and requires integration with traditional tools.
The final stage concerned the production of visual outputs. In this area, the difference between traditional approaches and AI systems is particularly evident.Traditional rendering allows precise control over materials, lighting, and viewpoints, but requires significant time and expertise. Generative systems, on the other hand, produce photorealistic images in very short timeframes from textual prompts or visual inputs.

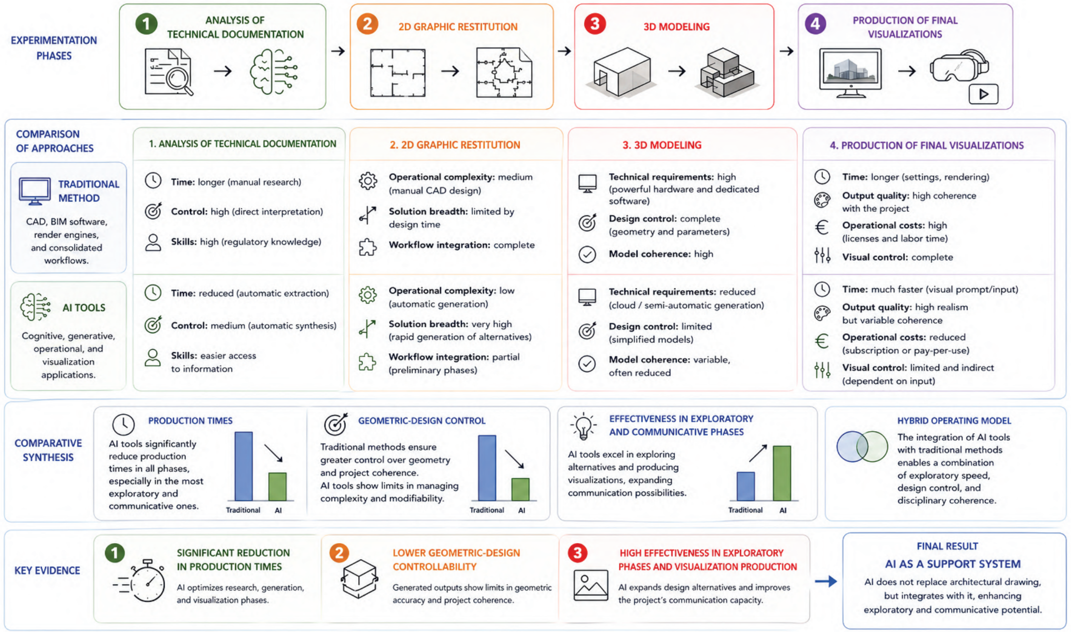

Fig. 7 - Comparative diagram of traditional methods and AI tools across the stages of architectural representation, highlighting their main impacts on time efficiency, design control, and communicative effectiveness.

However, despite their high visual plausibility, these outputs do not always align with the underlying design model, highlighting a significant distinction between visual quality and the main limitations.
Overall, the comparative analysis revealed a recurring pattern across all tested scenarios.
AI-assisted workflows consistently reduced the time required to produce visual outputs and significantly increased the number of design alternatives available during the exploratory phases.
At the same time, the experiments highlighted lower geometric controllability and reduced transparency of the generative process compared with conventional CAD, BIM, and modeling environments. The results therefore suggest that the principal contribution of AI lies not in replacing established representation methods but in extending their exploratory and communicative capabilities. Conversely, tasks requiring precise geometric definition, technical verification, and design consistency continue to depend strongly on the designer's expertise and on conventional representation tools.
The experimental evidence supports the interpretation of AI as a complementary layer within the architectural design ecosystem, where automation increases efficiency. At the same time, drawing retains its role as a critical instrument of control, validation, and disciplinary coherence.
The comparative assessment summarized in Figure 7 shows that the most significant advantages of AI applications emerge in production speed, exploratory capacity, and visual communication. Conversely, disciplinary reliability was associated

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with geometric controllability, semantic transparency, and consistency between generated outputs and design intent.

DISCIPLINARY IMPLICATIONS AND FUTURE DEVELOPMENTS

The experimental results show how introducing AI into architectural representation processes produces different effects across the various stages of the design workflow. Generative tools prove particularly effective in the early phases of analysis and ideation, enabling the rapid production of design alternatives and visualizations.
At the same time, recurrent limitations emerge: difficulties in managing complex configurations, geometric model simplification, and discrepancies between visual plausibility and design coherence.
These outcomes confirm that AI does not function as a substitute for the design process but rather as a computational environment that expands the design process's exploratory and communicative potential. Its effectiveness depends on the designer's ability to correctly define inputs and parameters, select data, and critically interpret outputs.This results in a shift in the designer's role from the direct production of images to the definition and control of the conditions that guide their generation.
The analysis, therefore, highlights a dual requirement: on the one hand, to enhance AI's contribution to design production and communication; on the other, to maintain a critical approach capable of governing its limitations and implications. In this context, skills such as prompt design, data selection, and output validation become central to the design process.
Future developments point toward greater integration of AI systems with advanced design environments, such as BIM platforms, parametric systems, and XR environments, shaping increasingly interconnected workflows. In this scenario, AI functions as a transversal layer that supports the entire process without replacing disciplinary

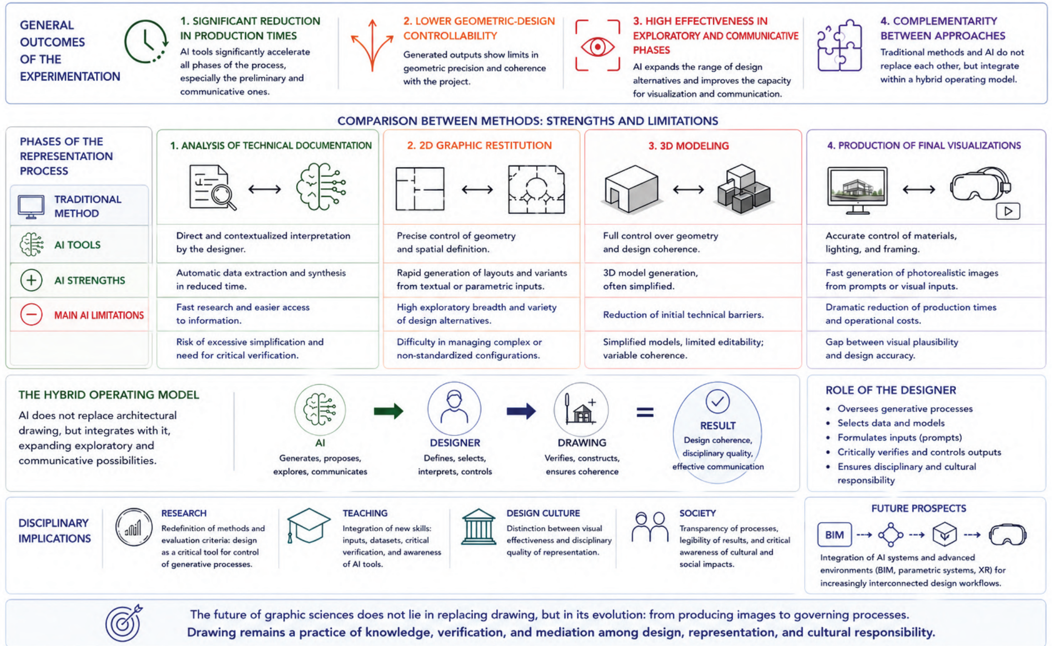

Fig. 8 - Disciplinary Implications and Future Developments of AI in Architectural Representation. The diagram summarizes the main outcomes of the experimentation, highlighting AI's role as a transversal support system, the shift toward a hybrid operational model, and the implications for research, education, design culture, and society.

logics (Fig. 8). The implications for architectural drawing can be grouped into four main areas. In research, there is a need to redefine methods and evaluation criteria, considering drawing not only as a representational outcome but also as a critical device for controlling generative processes. In education, it is essential to integrate traditional competencies with new skills for the conscious use of AI. In the cultural dimension of design, the distinction between visual effectiveness and disciplinary quality of representation is reinforced.
The increasing integration of AI systems into design practice also raises broader questions concerning the understanding and governance of complex technological environments. As highlighted by Parisi (2025), technological progress requires not only innovation but also the development of widespread forms of knowledge capable of critically interpreting and controlling increasingly complex systems.
Finally, at the social level, the widespread use of images and automated processes requires greater responsibility for transparency, readability, and critical awareness.
From this perspective, questioning the future of drawing means redefining its role within a complex digital ecosystem, where it continues to serve as a tool for knowledge, verification, and mediation among design, representation, and cultural responsibility.

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CONCLUSION

The comparative analysis conducted across the different stages of architectural representation revealed a recurring pattern in the interaction between traditional workflows and AI-assisted processes.
The experimentation showed that AI systems are particularly effective in accelerating the production of visual outputs, expanding the range of design alternatives, and supporting communication and visualization activities. At the same time, the results highlighted persistent limitations in terms of geometric controllability, semantic consistency, and transparency of the generative process. While AI significantly enhances exploratory and communicative capabilities, the reliability and coherence of the outcome remain strongly dependent on the designer's critical intervention.
These findings suggest that AI should not be interpreted as a substitute for architectural drawing, but rather as an additional operational layer within the contemporary design ecosystem.
The comparison between traditional and AI-assisted methods confirms that automation can support several phases of the workflow, particularly those related to ideation, visualization, and information management. Still, it does not eliminate the need for disciplinary knowledge, design judgment, and representational control.
The experimental evidence therefore provides a basis for a broader reflection on the evolving role of drawing in architecture and on the new responsibilities emerging from increasingly hybrid design environments.

"The Drawing is dead, Long live the Drawing!"

The apparent paradox in this formula does not signal the end of drawing but rather calls for its critical redefinition within the contemporary digital ecosystem. The advent of generative AI does not, in fact, cancel the disciplinary value of architectural drawing, but calls into question its operational habits, established conventions, and modes of transmission. If machines are now capable of producing increasingly effective and complex images, this does not imply the possibility of replacing drawing as a practice for interpreting, constructing, and verifying the project.
The central issue emerging from this reflection concerns the relationship between image generation and the control of meaning. In contemporary AI applications, the designer is no longer solely the one who directly draws the sign, but the one who establishes the conditions under which the image is produced, selected, interpreted, and reconnected to a coherent design process.
The question, therefore, is not whether AI can generate architectural images, but whether such images can truly acquire disciplinary value without a critical act of control, verification, and judgment. It is here that drawing continues to express its deepest function: not a mere means of formal representation, but a cognitive device through which the project is understood, measured, and made explicit.
The experimentation and comparison between traditional tools and AI systems clearly show that the automated production of images significantly expands the exploratory and communicative possibilities of design. Speed of generation, multiple alternatives, increasing accessibility, and the visual power of outputs are elements that cannot be ignored. However, these advantages further highlight a fundamental distinction: that between visual plausibility and design coherence. A convincing image is not necessarily a reliable representation; a formally effective configuration does not always correspond to a spatial, technical, or cultural construction that is effectively controlled. For this reason, drawing does not lose its centrality but rather redefines it at a different—and, in some respects, more demanding—level.
In this sense, the role of the designer also changes profoundly. Responsibility is no longer limited to direct control of representation tools but extends to defining the criteria, parameters, and constraints within which generative systems operate. The designer is now required to orient the process, select data, construct meaningful inputs, critically interpret outputs, and distinguish communicative effectiveness from disciplinary relevance. If the machine learns from correlations and returns plausible configurations, it remains the human task to assign direction, measure, and responsibility to the process.
The transition that emerges is therefore not from the centrality of the designer to their marginalization, but from direct control to a more complex and reflective form of governance of representation.
Several implications for research and education follow from this. In research, it is necessary to develop methods and evaluation criteria that consider not only the effectiveness of the produced image but also the degree of controllability, coherence, and transparency of the processes that generate it. In education, it now appears essential to complement traditional drawing skills with new competencies in prompt formulation, data construction and selection, critical reading of results, and verification of their reliability.
The aim is not to replace learning drawing with training in tool use, but to rethink the relationship between disciplinary knowledge and intelligent environments, so that new technologies can be integrated without impoverishing the cognitive quality of design.
It is from this perspective that Giorgio Parisi's reflections on scientific knowledge and technological transformation acquire particular relevance. Parisi has repeatedly emphasized that the increasing complexity of contemporary technologies requires not only technical innovation but also the widespread development of critical understanding and shared forms of knowledge capable of governing their effects. Applied to the field of architectural representation, this perspective suggests that the challenge posed by AI is not limited to adopting new tools, but also concerns the capacity to understand their mechanisms, evaluate their limitations, and critically interpret their outcomes.
Within architectural education, this implies the need to train capable designers not only to operate advanced digital systems but also to understand the cultural, methodological, and epistemological implications of their use.
The issue is therefore not exclusively technical. It concerns the conditions through which architec-

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tural knowledge is produced, communicated, and validated, as well as the responsibility associated with the increasing influence of automated systems on the construction of images, information, and design decisions.
In this sense, the integration of AI into representation processes raises broader questions regarding transparency, accountability, and the social interpretation of the environments that such technologies help shape.
For these reasons, asking today "what future" for drawing means not simply questioning the fate of a technique, but the future of a form of knowledge. Drawing continues to be the place where the project takes a position in relation to reality, confronts its constraints, and makes its construction process visible.
Even in increasingly automated environments, it retains its role as a critical mediator between conception, representation, and responsibility. Its future is therefore not played out in nostalgic defense of a gesture, nor in uncritical acceptance of emerging technologies, but in the capacity to redefine its role as a cultural, cognitive, and educational practice.
In conclusion, architectural drawing does not appear as a residue of the past, but as a competence destined to transform without losing its necessity. If tools change, the issues of control, judgment, and meaning remain open—and perhaps even more urgent today. It is in this persistence of its critical function that drawing can continue to constitute an essential resource for research, education, and design.
Rather than declaring its end, the current technological shift thus calls for clarification of what within drawing must be preserved, what must be transformed, and what new responsibilities it is called upon to assume in the near future.

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