A Framework for AI Upskilling in Architectural Design: Towards Effective Self-Learning

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Abstract

The integration of AI (Artificial Intelligence) into architectural design workflows offers transformative opportunities for the AEC (Architecture, Engineering, and Construction) sector. However, its adoption presents challenges, particularly regarding the upskilling of professionals who must navigate the complexities of AI while balancing practical learning constraints. This contribution examines AI upskilling in the AEC sector, emphasizing the integration of generative AI tools into the architectural design skillset. Additionally, the contribution proposes a workflow-based overview of conceptual design tasks that can be empowered by AI integration. A keyword-based system is introduced to organize AI-assisted design actions, offering a structured approach to personal skill development. This very limited framework aims to present an example to guide professionals in planning self-learning projects, helping them adopt AI technologies effectively while enhancing their existing expertise.

Keywords
AI, generative AI, generative design workflows, AI upskilling in AEC, AI teaching

Application of a GEN-AI script to generate a concept image (image by the author).

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Introduction

The integration of AI (Artificial Intelligence) in architectural design presents transformative opportunities, yet its adoption carries multiple challenges. In particular, as with any other technical expertise, AI integration in the practice demands for any actor involved to expand their skill sets, investing time and resources to learn the adequate know-how related to it.

This contribution is built on previous experiences [Cavaglià 2024], and it delves into the distinction between two fundamentally different, but complementary skill sets that support any form of digital expertise: the practical use of tools via GUIs (Graphical User Interfaces) and the development of custom functionalities through coding and APIs (Application Programming Interfaces). The first skill set, focused on GUI-based software usage, is widely accessible to most practitioners [Martinelli *et al.* 2024] and requires only a moderate learning curve. This accessibility makes it a practical and efficient solution for many tasks in architectural design and documentation. Conversely, the second skill set, customizing and extending digital tools through programming, requires advanced technical capabilities and specialized digital knowledge, which may not be realistic or necessary for most professionals in the field.

In the architecture and construction sectors, many design needs can be effectively addressed through software solutions equipped with intuitive GUIs. These interfaces empower users to operate complex software without requiring programming expertise, enabling professionals to focus on their primary tasks: design, visualization, and project management. However, the advantages offered by GUIs can also impose limitations. Since the commands available within GUIs essentially offer a finite set of predefined functions, there may be instances where a specific action that a designer wishes to perform is not included among the available options. Such instances can be solved only by actively generating the missing option using custom coding or scripting through APIs or other development tools, such as VPL (Visual Programming Languages) editors. These methods allow users to extend the functionality of the software beyond its standard capabilities, tailoring it to address unique or specialized requirements (fig. 1).

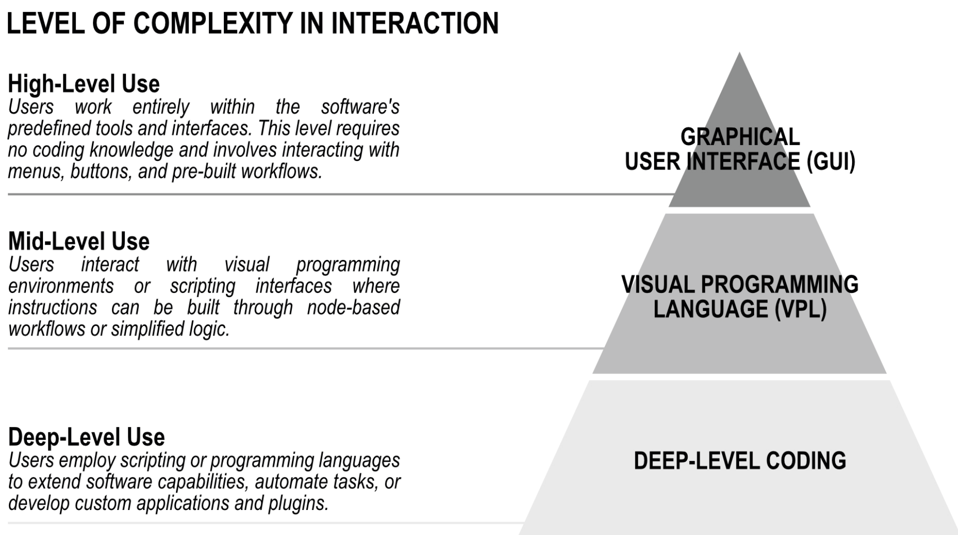

Fig. 1. Schema representing the different levels in interaction between human and software (image by the author).

Both approaches can support any stage of a construction project, but the rapid evolution of AI initially disrupted this established scenario of technological accessibility seen in recent decades. Early AI tools, being at the forefront of innovation, mandatory required deep coding expertise due to the extreme novelty of technology. This is because the rapid advancement of AI required software developers to take time in defining the path for integrating AI seamlessly into traditional user experiences, making such tools initially circulate mainly in the form of instruction packages to be directly implemented within coding environments.

AI implementation in design, challenges and opportunities

The implementation of AI in architectural design workflows is a complex issue, framed by Desouki *et al.* as both an opportunity and a threat. While AI enhances efficiency and fosters innovation by automating tasks traditionally performed by humans, it also poses the risk of rendering many previously essential skills less relevant to the point of potential obsolescence [Desouki *et al.* 2023]. AI is actually an umbrella term encompassing a wide spectrum of technologies and applications [Matter, Gado 2024], which have been positively leveraged within the AEC (Architecture, Engineering, and Construction) sector to enhance various facets of the design endeavor, including: early-stage conceptual design exploration [Bao, Xiang 2024; Edwards *et al.* 2024], design optimization [Alwetaishi, Shamseldin 2021], and project management [Senjak Pejić *et al.* 2023]. However, according to a report from the software developer *Snaptrude*, AI implementation have currently displayed the highest impacts within the design stages of PE (Pre-Design), Conceptualization, SD (Schematic Design), and DD (Design Development) [1].
As proposed by Li *et al.*, the conceptualization stage of a design project can be enhanced through the extensive solution exploration facilitated by generative AI platforms specializing in image content synthesis [Li *et al.* 2024]. Generative AI for image synthesis refers to a type of Artificial Intelligence that leverages algorithms, such as GANs (Generative Adversarial Networks), to create new visual content based on input parameters or datasets [Li *et al.* 2024]. Users typically provide text prompts, sketches, or reference images as input, and the AI generates corresponding outputs, such as detailed concept renderings or design variations, tailored to meet the specified criteria or creative direction. Like many other AI technologies, generative AI for image synthesis became widely accessible following the seminal release of the ChatGPT platform in 2022 and is part of the current wave of AI innovations relevant to the AEC sector (fig. 2).

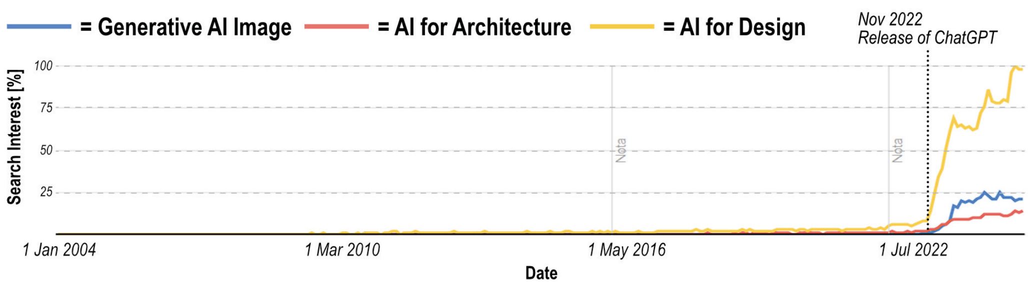

Fig. 2. Search trends for the selected keywords according to the statistics retrieved by *Google Trends* (image by the author).

The disruptive potential of AI technology, particularly in critical design phases such as early-stage conceptualization, has driven many professionals in the AEC sector to grapple with the need to acquire new skills. While the adoption of AI offers opportunities for innovation and efficiency, it also poses challenges, including the demand for professional upskilling. However, the push for these updates to professional know-how conceals an insidious threat.
One major issue lies in the accessibility and usability of AI platforms. As initially observed, many applications characterizing the first wave of AI services did not feature user-friendly GUIs similar to legacy software in the AEC industry. Instead, a significant portion of the available documentation was aimed at coders and data scientists rather than designers. In many occasions immediate access to such information creates both

a gap, and a bias, during the learning process of AI technologies, which may potentially alienate professionals whose focus lies on creative and strategic tasks rather than programming. This is a notably relevant issue, as a significant proportion of professionals update their AI skills in a self-taught manner. In such a context, wrongly acquired biases about the technology or its use may remain unresolved due to the lack of human feedback on the matter. A survey involving responses from over 1,200 professionals across 50 countries (35% from the United States) revealed that AI tools are widely adopted, with over 70% of participants using them in some way. However, nearly 68% of them acquired their expertise without any formal training [2]. This information provides a twofold perspective. On one level, it highlights the necessity and interest in experimenting with such technologies, while on a deeper level, it suggests that these efforts are often the result of self-driven learning.

The challenge of learning AI-oriented skills

Self-learning in AI, as in any discipline, demands a structured approach that aligns with an appropriate learning curve to ensure its effective application. In this regard, the relevance of the aspect of learning in the adoption of AI within the AEC sector has been documented by different studies. This issue has become central to contemporary AI discussions, as technology's maturity has progressed to the applicative stage. An interesting example for observing this shift in perspective could be the work of Gero, which proposed in 1991, a review of ten relevant problems for AI in design, all which related to AI development as a concept, or a technology [Gero 1991]. These same problems are then examined by Zwierzycki in 2020, who, while acknowledging that many of them remain relevant to the contemporary development of AI, introduces a completely novel perspective. This perspective addresses not only the development of AI but also the challenges tied to its adoption, citing education as a pivotal element capable of influencing its trajectory [Zwierzycki 2020]. Otanayo advocates strongly for addressing the problem of AI adoption by focusing on the development of adequate learning strategies tailored on the specific needs and characteristics of operators, and students, of the AEC sector [Onatayo *et al.* 2024]. However, while the review of teaching curricula can address the needs of students within educational institutions, the same cannot be said for the many active professionals whose self-learning practices, by definition, rely on personal experience and intuition. Different studies propose the implementation of workplace training courses on AI technologies as a solution for upskilling professionals [Bogoslov *et al.* 2024; Chetty 2023]; however, while this strategy inherently contradicts the framework of self-learning and clashes with the potential constraints of small offices with few workers, it can serve as a reference for extracting key insights to propel continuous learning.

An overview of a task-level study focused on workflow objectives

Huang *et al.* provide a notable example of academics reflecting on the downside of AI adoption, particularly the risk of professionals being replaced in their jobs by machines due to skill obsolescence. In their Theory of AI Job Replacement, Huang *et al.* predicts that AI replacement mainly functions at the task-level, rather than at the job-level [Huang, Rust 2018]. Huang deepened this concept, noting that AI development progresses in a sequential order, starting with routine, low-complexity tasks, followed by rule-based tasks, and ultimately advancing to more intricate, cognitive, and creative functions. Consequently, the upskilling of professionals should focus on acquiring knowledge in AI technologies that support the initial stages of progression while also enhancing personal expertise aligned with the more advanced stages. This is because the initial tasks are more easily supported by AI, while the latter are the least. This insight is also supported by separate studies. For example, Sourek notes how AI excels at iterative, parametric, and quantitative tasks but lacks genuine creativity or poetics, and even

noteworthy outputs such as synthetic conceptual images can only serve as incomplete suggestions for the designer to reflect upon and personally adjust into a broader design process [Sourek 2024].
In the context of architectural design supported by a digital environment, a task can be transformed into the concept of a workflow. A workflow is a set of procedure defined to achieve a goal and produce a specific content [Tuijn 2003]. Workflows can be defined at various levels, such as at the project level (e.g., site analysis, concept creation) or at a more detailed level with narrower scopes (e.g., 3D texturing, print layout setup). Professionals should prioritize upskilling AI implementation in workflows with low complexity or high repetitiveness, as these are ideal for automation. A clear map of AI-enabled workflows is essential to identify and optimize tasks for automation effectively.

Partial mapping of AI-enabled digital workflows for architectural design

The present overview of AI adoption has been simplified to focus on the issue, framing a set of priorities. AI upskilling could be planned around workflow optimization by integrating AI at a workflow level and targeting workflows with higher potential for effective automation or support via AI. These workflows, however, should not be too broad in scope but rather narrow. For example, instead of automating conceptual design as a whole, specific substeps should be addressed, such as image color correction, image upscaling, content removal in concept views, and so forth. Even complete conceptual image generation is just a small sub-operation within this framework. The synthetic image can only be considered a viable design option after being processed into subsequent steps of the design workflow, where the designer supervises and scrutinizes the content, optimizing it to create a feasible and constructible design. This ensures the inclusion of a human-in-the-loop component.
To lessen the steepness of the learning process, AI adoption should also initially target digital environments able to provide a well-defined GUI (figs. 3, 4), since software with well-designed GUIs can foster quicker adoption and improve user performance [Peng 2024; Staggers, Kobus 2000].

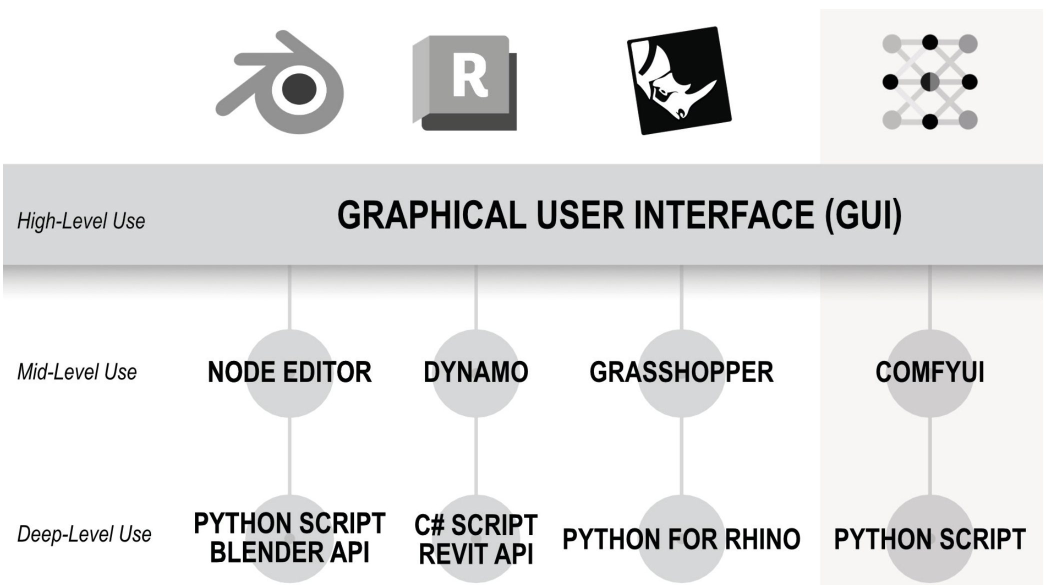

Fig. 3. Example of the different levels in interaction between human and software. The image lists relevant alternatives of digital tools able to support architectural design. Starting from the left, *Blender*, *Revit*, and *Rhinoceros*. At the right side, the picture list one sole option of integrate digital environment where implement AI-based generative processes for image synthesis, in the form of the platform of *Stability Matrix* (image by the author).

Once the working environment is selected, target workflows can be studied and adopted on a case-by-case basis, provided they integrate seamlessly into the chosen environment. Generative AI-based platforms are typically categorized by the main type of input they require and the output they generate. For example, generative AI platforms for image

synthesis which process textual prompts to produce corresponding images, can be categorized as AI-tool which request text as input, and image as output, which can be shortened to the label text-to-image (fig. 5). Implementing this labeling ruling to online search queries can rapidly support a search for the specific type of tool needed, for example image-to-image may guide towards the AI-tools able to edit existing pictures.
The final step in planning a self-learning process for AI involves identifying and addressing the specific workflows to acquire. In this context, the study provides partial lists of workflows in figures 6 and 7, which serve as valuable resources. These workflows can be accessed

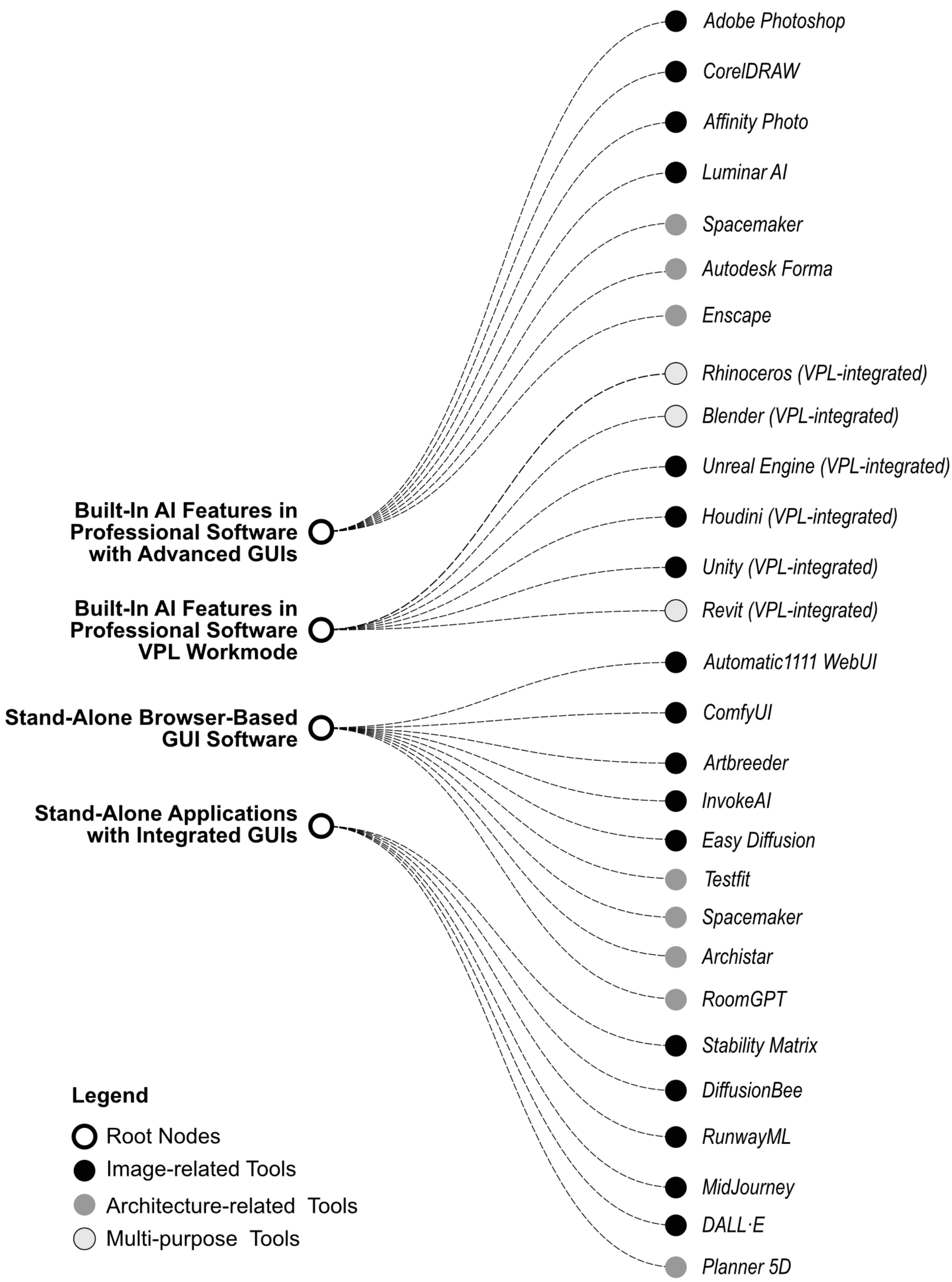

Fig. 4. Partial list of noteworthy AI-tools with potential application in an architectural design process (image by the author).

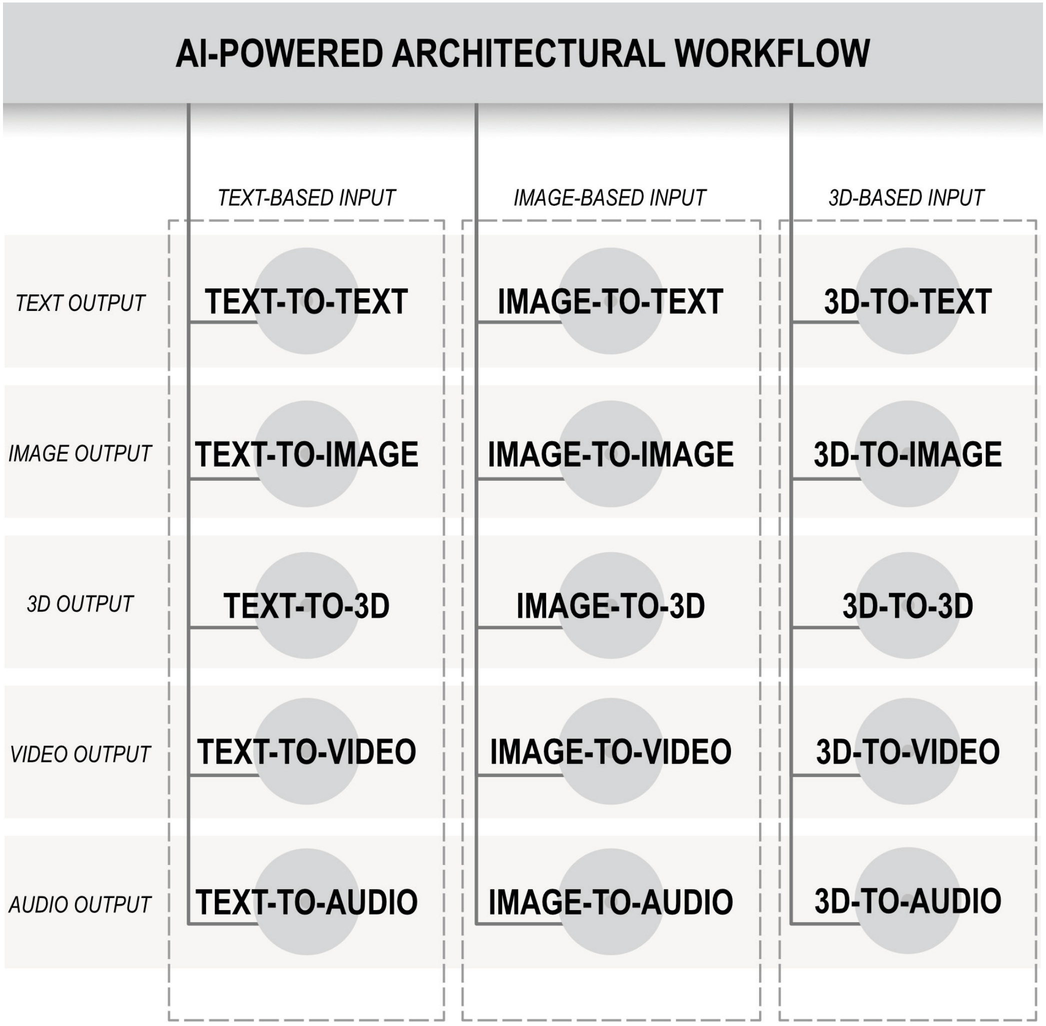

Fig. 5. Schema about the ruling for forming the label able to identify AI tools based on generative paradigm (image by the author).

and combined strategically to structure an effective study plan, ensuring that the learning process aligns with practical applications and targeted objectives. It is important to note, however, that such lists represent only the results of unstructured investigations, and further research is necessary to provide a more robust array of the workflow currently enabled by AI tools. In conclusion, it is important to highlight that the presented framework, although limited in scope, can be readily applied to AI LLM (Large Language Model) platforms to guide the formulation of queries tailored to create a specific study plan. In this context, the presented workflows become keywords that steer the generative process of AI toward more specific objectives [Ceccon 2023].
It is proposed that the insofar outlined framework can be applied to target the integration of AI tools into specific phases and tasks of the architectural design process. Taking as a reference a typical design workflow in the architectural field, which starts from the pre-design phase, and proceeds through concept design, early-stage design, and schematic design, the framework allows for a systematic identification of complex activities that can be supported or enhanced by AI applications.
For instance, in the pre-design phase, the task of site analysis may be broken down into subtasks such as data collection, spatial and morphological evaluation, regulatory analysis, and the synthesis of findings into visual and textual outputs. By mapping each subtask, to the tasks lower level of complexity, it becomes possible to pinpoint where specific AI techniques, such as computer vision, machine learning, or natural language processing, can support or automate

TEXT-TO-TEXT

Text Summarization	*Automatically summarizes lengthy architectural documents, reports, or regulations into concise overviews.*
Sentiment Analysis	*Analyzes textual feedback to identify positive, negative, or neutral sentiments.*
Named Entity Recognition	*Extracts key entities such as locations, materials, building types, or project names from text.*
Document Clustering	*Organizes large sets of textual documents into thematic clusters.*
Knowledge Graph Generation	*Extracts relationships between entities and maps them in a structured knowledge graph.*
Text Sentencing and Parsing	*Breaks text into sentences, parts of speech, or structured data.*

TEXT-TO-IMAGE

Text-to-Image Generative Syntheis	*Generate architectural visuals or sketches from textual prompts.*
Text-Based Image Style Control	*Modify images using descriptive prompts, e.g., "Gothic style," "modern minimalism", etc…*
Text-Based Texture Syntheis	*Genrate texture image for CG implementation, i.e., seamless texture, albedo map, etc…*

IMAGE-TO-IMAGE

Image-to-image Generative Syntheis	*Modify existing visuals with AI-driven changes.*
Inpainting	*Fill missing parts, fix errors, or alter selected boundaries in images.*
Outpainting	*Extend images beyond their original frame.*
Style Adaption	*Apply artistic or architectural styles to images.*
Relighting	*Simulate new lighting conditions, such as daylight, night.*
Upscaling	*Enhance image resolution for higher-quality visuals.*
Background Removal	*Remove background environment to isolate an image element.*
Colorization	*Convert grayscale images to full-color renderings.*
Denoising	*Reduce noise or artifacts in images.*
Edge-to-Image Generation	*Turn sketches or outlines into realistic architectural visuals.*
Deblurring, or Refocus	*Deblur an image by restoring optimal image shaprness. At higher level, fit differently the image focus.*
Texture Variation	*Generate variation of target texture, e.g., alter material color, alter material surface type, etc…*
PBR Texture Map Generation	*Create image maps from input image, e.g., normal map, cavity map, occlusion map, etc…*
Texture Style Adaption	*Alter the graphic style of atexture image, e.g., conceptual, photorealistic, toon, etc…*

TEXT-TO-3D

Text-to-3D Generative Syntheis	*Generate 3D models from textual descriptions.*
Voxel-Based Design	*Generate voxel-based structures or models.*

IMAGE-TO-3D

Image-to-3D Generative Syntheis	*Generate 3D models from single or multiple 2D images.*
Depth Map Extraction	*Generate depth information for perspective or 3D conversion.*
Point Cloud Reconstruction	*Convert images into a point cloud for 3D visualization.*
AI-Based Photogrammetry	*Recreate 3D volumes from image sequences or photographs.*
Texture Mapping	*Apply textures extracted from 2D images onto 3D surfaces.*

3D-TO-3D

Mesh Retopology	*Automatically improve or simplify 3D meshes.*
Performance Optimization	*Optimize designs to improve one, or multiple, performance parameter.*

Fig. 6. Partial lists of the workflows associated with the AI tools based on the following paradigms: text-to-text, text-to-image, image-to-image, text-to-3D, image-to-3D, and 3D-to-3D (image by the author).

3D-TO-IMAGE	
AI-Enhanced Rendering	*AI-aided rendering of 3D models.*
IMAGE-TO-TEXT	
Object Recognition	*Identify and classify objects within an image, storing data such as, number of objects, surface area in image, location in image, etc…*
Image Classification	*Sort image-based dataset using specific categories.*
Semantic Segmentation	*Segment images into regions corresponding to specific components, or classes of elements.*
Caption Generation	*Automated generation of textual descriptions for images or scenes.*
Visual Annotation	*Automatically label design components in architectural plans or renderings.*
TEXT-TO-AUDIO	
Voice Synthesis	*Generate audio speech from text file script.*
IMAGE-TO-AUDIO	
Environmental Sound Syntheis	*Generate background envirnmental audio fitting the context of a given image.*
TEXT-TO-VIDEO	
Text-to-Video Generative Syntheis	*Generate architectural video or animation from textual prompts.*
VIDEO-TO-VIDEO	
Video Upscaling	*Enhance video resolution for client presentations.*
AI Frame Interpolation	*Smooth or increase frame rate for animations.*
Relighting in Videos	*Dynamically adjust lighting across video frames.*

Fig. 7. Partial lists of the workflows associated with the AI tools based on the following paradigms: 3D-to-image, image-to-text, text-to-audio, image-to-audio, text-to-video, video-to-video (image by the author).

well-defined portions of the process. AI can, for example, extract spatial features from satellite images, analyze planning documents to extract zoning constraints, or generate summary reports combining maps and descriptive content. Through this simulation, the framework not only highlights opportunities for task enhancement but also reveals learning targets for professionals aiming to build AI-related competencies (fig. 8).
These targets may include acquiring skills in AI-enhanced GIS workflows, regulatory document parsing via NLP (Natural Language Processing), or clustering and classification techniques for morphological analysis. A crucial step in applying the framework effectively lies in the accurate identification and classification of input and output data, which serves as the foundation for selecting appropriate AI tools. Regardless of the design phase or task under consideration, understanding what type of data is available (input) and what type of result is expected (output) enables the narrowing down of possible AI methods. To streamline this process, both inputs and outputs should be sorted into macro-categories: image, text, audio, 3D, and video. This classification not only simplifies tool selection but also aligns the technical potential of AI systems with the data's inherent structure, ensuring that the tools employed are well-suited to the nature of the task. For example, a task involving georeferenced images and visual analysis clearly calls for image-based models, while a zoning code analysis falls under text-based processing.
By applying the framework in this way, self-learning efforts can be directed toward purpose-driven, context-aware applications of AI in architectural design, aligning technological proficiency with domain-specific workflows.

Conclusions

This contribution has examined the role of AI upskilling in the AEC sector, with a particular emphasis on integrating generative AI tools into the architectural design skillset. It addresses a critical challenge of our time: the need for seasoned professionals in the

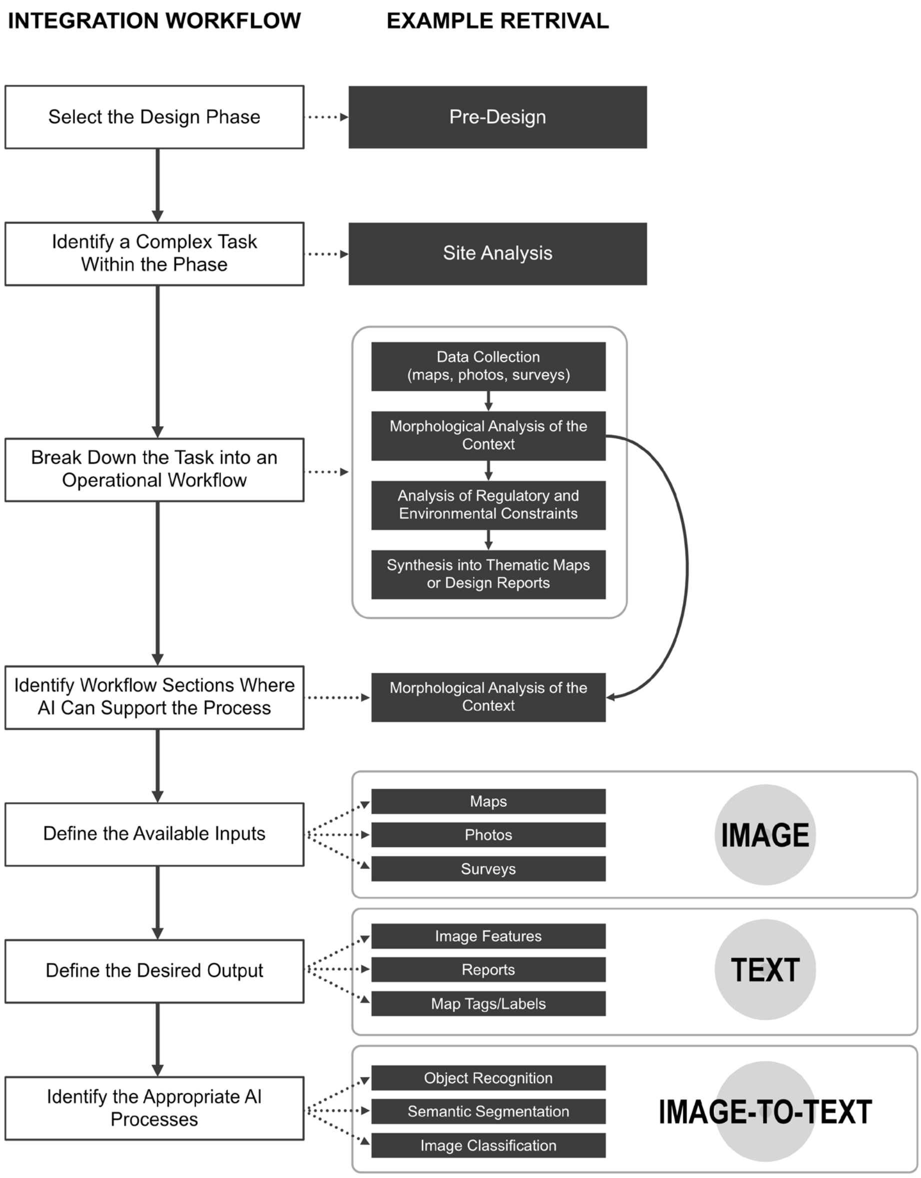

Fig. 8. Simulated workflow application for targeting self-learning objectives through the integration of AI-supported actions within architectural design tasks (image by the author).

sector to navigate the complexities of the AI revolution and pursue the advantageous adoption of new knowledge and technologies. While this issue may appear straightforward, given that AEC professionals are inherently driven by the need for continuous learning and adaptation, the unique nature of AI tools as novel technologies introduces a degree of uncertainty that surpasses typical professional updates. This uncertainty arises because even the teaching channels and learning frameworks are still adapting to the rapid pace of AI innovation, making the development of a feasible and effective self-learning plan a complex task.

In this context, the contribution seeks to simplify the matter by reframing the issue from a more familiar perspective. Specifically, it encourages viewing AI-based technologies as new additions to the array of digital tools available for architectural design, rather than as a disruptive, standalone domain. By shifting the focus from AI development to AI utilization, the discussion aims to empower professionals to approach these technologies as practical tools that complement their expertise, rather than as abstract challenges requiring entirely new paradigms of learning. In this regard, a workflow-based overview is presented for listing the possible fundamental tasks of an architectural design workflow in the conceptual design stage, which may be empowered by AI integration and support. It is proposed in this setting that a keyword-based system organizing the specific design actions which can be performed by AI tools can guide the plan for a personal project of self-learning and skill update.

Notes

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