

Artificial Intelligence and AECD Project: mapping the application of AI into a structural framework for designs

Inteligência Artificial e Projetos AECD: mapeamento para aplicação de IA em um framework de estrutura de projetos

Leonardo de Oliveira Gomes

Universidade Federal de Minas Gerais

<https://orcid.org/0009-0001-9828-9249>

leo.design.ufmg@gmail.com

Andréa Franco Pereira

Universidade Federal de Minas Gerais

<https://orcid.org/0000-0002-3633-4884>

andreafranco@ufmg.br

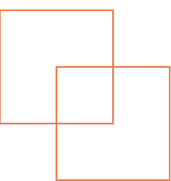
Abstract

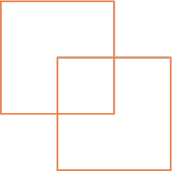
Research into digital design assistance and artificial intelligence (AI) is not new. Advances stemming from them have strongly marked our way of developing projects, reaching the potential for disruptive and discontinuous creations, far beyond what we know in the world. AIs have plenty of room to grow, and within decades intelligent machines could possibly surpass human intelligence. But first there will be a significant disruption in the way we behave, practice, and learn. We need to understand how to deal with this advance. This study is interested in expanding and diversifying the use of AI in the design practice of Architecture, Engineering, Construction and Design, proposing an introductory mapping (basic framework) of which AI-based systems, services, and artifacts actually assist, affect, and are available for use by designers, along with what changes in design practice with regard to conceptualization, interpretation, functionality, and performance, the natural requirements of AECDD projects.

Key Words: AEC projects; Digital Technology, Artificial Intelligence; Frameworks; Complexity

Resumo

Pesquisas sobre auxílio digital de projeto e inteligência artificial (IA) não são novas. Avanços oriundos delas marcaram fortemente nossa forma de desenvolver projetos, atingindo potencial para criações disruptas e descontínuas, muito além do que conhecemos no mundo. As IAs apresentam campo hábil para crescer sendo que em décadas máquinas inteligentes poderão possivelmente superar a inteligência humana. Mas antes uma interrupção significativa acontecerá nos nossos modos de comportamento, prática profissional e aprendizado. É preciso compreender como lidar





com esse avanço. A esse estudo interessa a ampliação e diversificação do uso das IAs na prática projetual da Arquitetura, Engenharia, Construção e Design, propondo um mapeamento introdutório (framework básico) sobre quais sistemas, serviços e artefatos baseados em IA realmente auxiliam, afetam e estão disponíveis para uso pelos projetistas, bem como o que muda na prática projetual no tocante à conceituação, interpretação, funcionalidade e desempenho, exigências naturais dos projetos de AECDD.

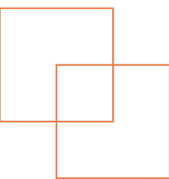
Palavras-chave: Projetos AECDD; Tecnologia Digital, Inteligência Artificial; Frameworks; Complexidade.

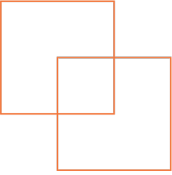
1 - INTRODUCTION

Research on design-aid systems and artificial intelligence (AI) is not new; some of it dates back over 60 years. And all the technological advances arising from these areas have significantly impacted the way we develop projects. The personal computer, CAD (Computer Aided Design), NURBS (Non-Uniform Rational Basis Spline) surfaces, and BIM (Building Information Modeling) are some examples. However, the use of AI-supported systems has currently gained prominence. A recently released text-based AI model achieved a record 1 million registered users in just five days.

Design-aid systems have historically incorporated advances in information technology and algorithms focused on, for example, 3D modeling, dimensional databases, or CNC (Computer Numeric Control). Today, embedded AI modules or applications are a definitive part of the evolution of these applications. According to Mielke (2021), embedded artificial intelligence (AI) is that which is dedicated to performing a single task in an extremely efficient and valid manner. It is known as Artificial Narrow Intelligence (ANI) and falls into the class of so-called Weak AI (WAI), representing, despite everything, the only type of AI currently available for projects.

Ludemir (2023) notes that there are truly no algorithmic solutions for the vast majority of problems we face in the world; in other words, it is not yet possible to write programs to solve them





all. However, the availability of enormous volumes of data (information) about these problems makes it possible to train specific algorithms (which we can write) so that machines can learn from them. For Goodfellow (2017), the difficulties faced by systems that rely on codified knowledge suggest that AI systems need the ability to acquire their own knowledge by extracting patterns from raw data. This training is achieved through machine learning (ML), and its development has currently demonstrated significant progress with numerous valid applications and artifacts, even for domestic use. As a result, machines are learning to identify, process, and act on our life patterns and behavior. However, Kissiger et al. (2021) claim that AI cannot "think" or will never act exactly as a human mind does. However, the accumulation of correspondences with patterns of human reality by AI models could approach and sometimes exceed the performance of human perception and reason.

Mielke (2021) states that we have reached a point where AI has room to grow, and within a few decades, these intelligent machines could quite possibly surpass human intelligence. But before that happens, a significant disruption will occur in our lifestyles, behaviors, jobs, and education. It is therefore also necessary to understand what lies ahead and how we can deal with this progress.

In this light, the present study focuses on discussing this expansion and diversification in the use of AI systems in design practice for the fields of Architecture, Engineering, Construction, and Design (AECD). While of enormous importance and relevance, not all ethical and social issues regarding AI will be addressed here. The research objective is to provide an introductory mapping (a basic framework) of which AI-based systems, services, and artifacts truly assist, impact, and, most importantly, are available for use by project stakeholders. The initial questions concern what changes in design practice with the introduction of these technologies regarding conceptualization, explainability, interpretation, functionality, and performance of projects—characteristics that are natural requirements of AECD development processes. Based on the analysis and structuring of AI-related technologies for design practice, a framework identifying AI use and integration relationships will be presented. Figure 1 presents the development flow of this study:

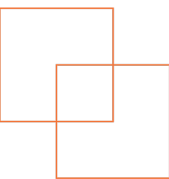
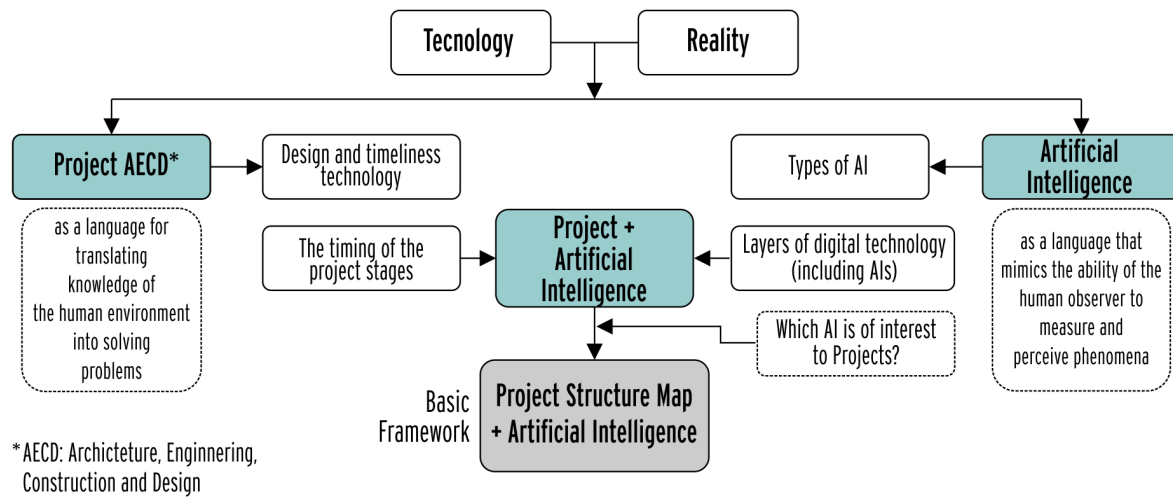


Figure 01 – Study development framework.

Source: Created by the authors.

2. TECHNOLOGY, THOUGHT, AND PERCEPTION OF REALITY

An interesting point in an analysis of concepts about technology and human thought is reality checking. Kissiger et al. (2021) explain that the current stage of AI development, driven by new algorithms and greater processing capacity, actually defines a new and extremely powerful mechanism for exploring and reorganizing reality. An AI accesses reality differently than humans do, making its advent a truly historical and philosophically significant milestone in the history of human thought. But after all, how do we perceive our reality?

Kissiger et al. (2021) structured a path that historically and chronologically addresses the relationship among human thought, the development of technologies, and perceived reality. According to them, a search for understanding the nature of reality can be observed for each era or civilization, with each one developing a set of adaptations and behaviors related to the prevailing environment. Individual human reasoning is highlighted for its ability to develop structures of understanding that act immediately at each moment, shaping what we know as the world. However,

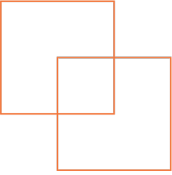


the rise of digitalization and the use of AI have produced truly new phenomena, not simply more powerful or efficient versions or simulacra of past events. Han (2017) comments that, when we begin to exist digitally, we disembodiment and become the flow itself, perceiving the world differently than it was previously known as something tangible and material. In this new digital world, the real and the virtual are blended, making it no longer meaningful to separate them. Human activity occurs in transition, but with strong signs of an imminent fusion, in which reality and truth will also become part of the flow and can be manipulated. According to Han (2017), we are not naturally (biologically) prepared for this kind of union that reconfigures the entire way we see the world. We still need to learn about the intermediation of non-things; we still need to understand how to deal with the intermediary possibilities of this new world that does not provide a distinction between the real and the virtual, between the tangible and the intangible. The main transition involves the concept of territory in the physical and tangible world, where life continues under a visual, sensory, and informational relationship between society and reality, to a new concept that migrates to an intangible territory, where life is daily induced by digital corporations, with the gradual loss of society's visual, sensory, and informational relationship, to a virtual, intangible, and metaphorical environment. AIs represent the new and powerful player in this quest, making it necessary to understand how significant this evolution is and under what criteria it is impacting everyone's lives.

3. DESIGN PRACTICE

Projects, as we know them, have always operated from a place of certainty, with real, tested, validated, and inherited solutions. Digital design assistance is valuable and irreplaceable. But how, as designers, will we deal with mediations and decisions based on non-things? In the relationship between reality and technology, a common thread stands out: the relevance of technology's role in the evolution of thought. With each step of the technological revolution, evolutions in thought can





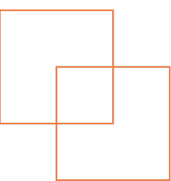
be associated. In this context, design practice has been present throughout humanity's historical cycle, as a parallel language, associated with problems and their solutions.

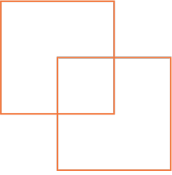
Structuring and planning projects in controllable phases is a basic rule of practice. Each phase is organized based on the control of the flows of information, matter, and energy, a universally accepted premise found in extensive literature on projects. These projects can be understood as languages, as they represent a systematic means of communicating ideas or propositions through conventional signs. Thomsett (2010) states that a project itself is temporary and non-recurring by nature. Added to this is its interdisciplinary and/or transdisciplinary nature, confirming its high degree of complexity.

The advent and progress in managing information in digital format have significantly impacted project development. However, the common thread uniting the different elements of this revolution lies in the effect of a transition from goods and services to information, generating "new interconnected products," characterized by large-scale hybridization fusing code, software, hardware, and behavior, creating another metaphor for our reality. Everything becomes a flux. For Kelly (2017), this constant flux does not simply imply that "things will be different," but rather that processes—the drivers of flux—are more important than products.

4. ARTIFICIAL INTELLIGENCE

A superficial historical approach to the development of AI is relevant, given the recent media explosion surrounding it. Kissinger et al. (2021), Pineau et al. (2021), Prunk et al. (2020), and Raghvan et al. (2020) report that many of the current criticisms, policy positions, and interventions on algorithmic accountability implicitly assume that AI systems work. They are defended by narratives of superhuman capabilities, broad applicability, and consistency, presented in corporate marketing materials and even academic research. However, as a neglected aspect of AI policy, functionality is often presented as a secondary consideration to other ethical challenges.

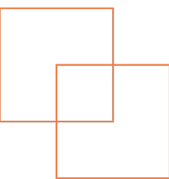


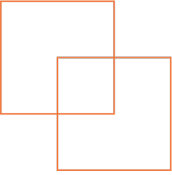


Historically, the term dates back to 1956, when this field of knowledge was created. Generically defined, AI corresponds to a set of techniques for building machines capable of solving problems that require human intelligence. According to Barbosa (2020), AI is linked to Computer Science and is associated with such issues as language, intelligence, learning, and problem-solving. In fact, the goal of AI is to understand and build "supposedly intelligent" systems capable of assisting in decision-making and controlling complex actions by simulating a "reasoned" solution to a problem.

In the early 1990s, AI studies reemerged in an applied form, after a long period of research without consistent results. Emerging computer networks at the time used AI principles to optimize navigation and indexing systems. Barbosa (2020) also mentions that in the 1990s, the internet, in its early days, also relied on AI studies for its optimization and commercial dissemination. From the 2000s onward, development was marked by an increase in the number of studies, applied tests, and commercial availability of related products. From the 2010s onward, we were marked by popular access to the practical results of AI research, with the possibility of using generative systems for AECD, the manipulation of massive amounts of data, virtual home assistants, and recently, the availability of natural language systems and generative applications based on massive amounts of text. It is important to note that the progressive gain in autonomy achieved by technology is noticeable. With each evolutionary step of AIs, an exponential increase in the autonomy of these systems is diametrically linked to the decision-making power of users. This is significant when it comes to design practices.

AIs follow an inevitable path in their evolutionary stages, and although Goodfellow (2017) argues that everyday life requires an immense amount of knowledge about the world, some of which is based on subjective and intuitive knowledge (i.e., difficult to articulate formally by a digital system), what we have witnessed is an intense effort to empower digital systems with an understanding of human reality, training AIs to simulate our power of abstraction, learning how to fill gaps that only a human observer can perceive in the phenomena of the world.





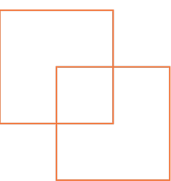
5. THE UNIVERSE OF ARTIFICIAL INTELLIGENCE: TYPOLOGY AND APPLICATIONS

Scott (2023) defines AI as a broad category of technologies whose goal is to automate tasks by mimicking human behavior. These adjacent technologies are experiencing rapid growth in applicability. As a result, we have reached a point where almost everyone interacts with them daily, often without realizing it.

The main categories, or drivers of AI development, include: a) machine learning, b) neural networks, c) computerized visualization systems, and d) natural language processing systems. Table 1 briefly describes these development categories.

Table 01 – Artificial intelligence research typology

Name	Description
Machine Learning (ML)	Training and algorithms to learn from data and make predictions or decisions without being programmed. Examples: recommendation algorithms, fraud detection, and image recognition.
Neural Networks	AI models inspired by the structure and function of the human brain, used in image recognition and natural language tasks.
Generative Adversarial Networks (GANs)	A subset of Neural Networks, where two networks compete against each other. Examples: generating images, creating deepfakes, and generative systems for AECD.
Deep Learning (DL)	A subset of Machine Learning, to process and analyze complex data. Examples: autonomous vehicles, language translation, among others.
Natural Language Processing (NLP)	AI model focused on understanding and generating human language. Examples: customer service chatbots, generative chatbots from text, virtual assistants Siri or Alexa, and language translation tools.



Speech	Recognition	AI that converts spoken language into written text. Examples: voice assistants, voice controls, and speech-to-text transcription.
Computer	Vision	AI model that understands and interprets visual information from images or videos. Examples: Facial recognition, object detection, and autonomous vehicle perception systems
Expert	Systems	AI models that mimic human expertise in a specific domain, using knowledge and rules to make recommendations or decisions. Examples: Medical diagnostic systems, financial planning systems, AECD creation aids, and customer support chatbots.
Robotics	AI	AI models used in robotics, enabling environmental recognition, decision-making, and the execution of physical tasks. Examples: Autonomous robots, drones, and industrial robotic assistants.
Generative	AI	AI models capable of generating text, images, or other media in response to requests in plain language.
Reinforcement	Learning	AI models that train an agent to make decisions in an environment, with feedback in the form of rewards or penalties. Examples: Games, autonomous robots, and optimization algorithms.

Source: Prepared by the authors

Other fields or research models are developed within these AI categories or are created from proposed relationships between the original engines. For example, there are Supervised Learning Systems, in which a human labels the training data (a closed training model). By contrast, there is also a chatbot based on a Large Language Model that uses large data repositories or the internet and is trained by thousands of people (an open training model).

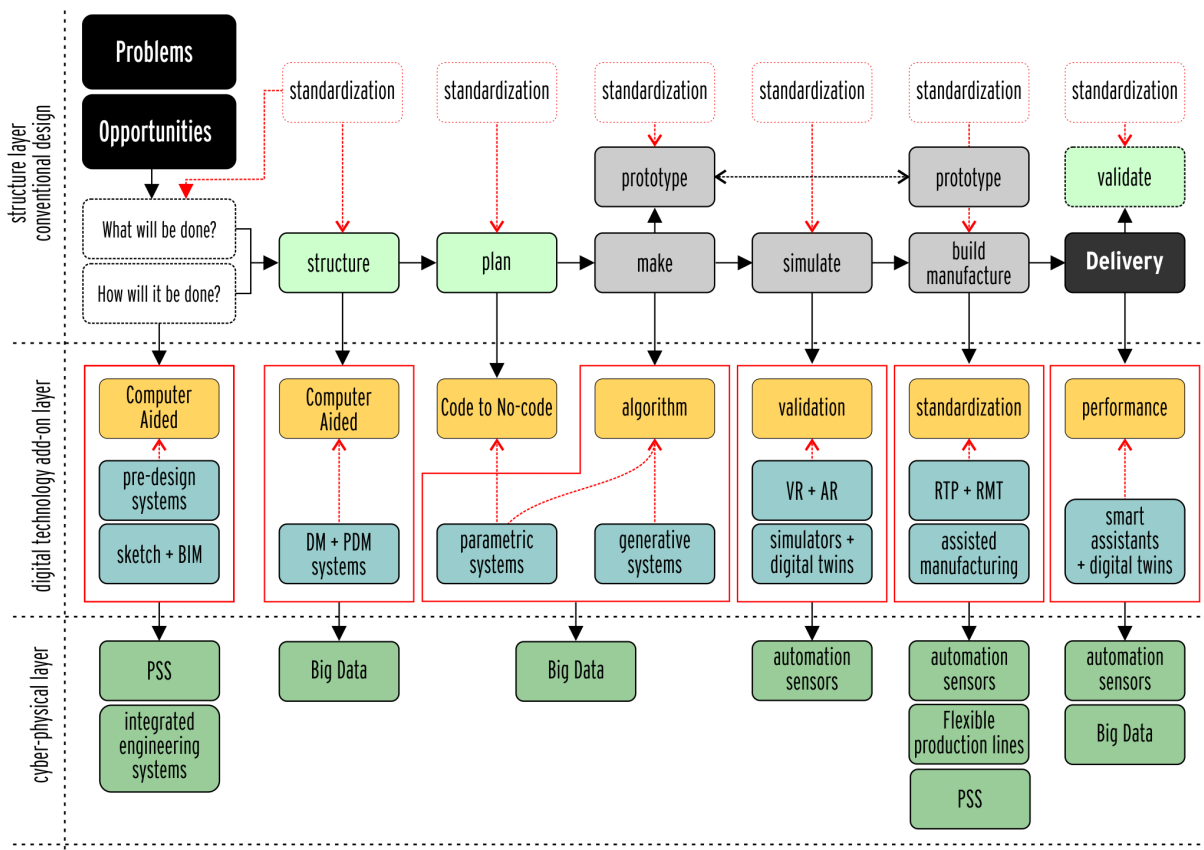
In fact, we have reached such a high level of algorithm-artifact integration based on and/or guided by AI that it is quite difficult to identify a single working model. However, current AIs are specific, as they perform cognitive activities without being accompanied by semantics or attribution of meaning.



6. THE PROJECT AND CURRENT TECHNOLOGICAL DEVELOPMENTS

As digital technologies evolve, new layers of processes are added. Figure 2 represents the inclusions of the first two layers to the project structure, resulting from the digitalization processes we've undergone.

Figure 2 – Representation of the evolution of the project structure, from the conventional layer to the adoption of digital assistive technology layer.



Source: Created by the authors

The evident involvement of digital assistance in all phases of an AECD project structure is evident, and the diagram appears systemic in addressing all stages. Descriptions of the Cyber-Physical layer are presented in Table 2.



Table 02 – Definitions of the digital technology classes presented in Figure 2.

Classes of Technology	Descriptions and Applications
Computer Assistance	Includes classes derived from Computer Aided Design (CAD) systems. CAD is based on LISP, the first kind of programming language for AI research since the 1970s.
Pre-Design System	Includes classes related to geoprocessing and bioclimatic engineering.
Sketch Design	Includes classes geared toward concepts and design sketches.
Data Mining + Data Product Management	DM + PDM: Includes classes of systems related to information management.
Parametric systems	Includes classes of systems related to automation.
Generative systems	Includes classes of systems related to the generation of algorithmic solutions, with input from designers.
Virtual Reality + Augmented Reality	VR + AR: Includes classes of systems related to the representation and early viewing of designs.
Simulators	Includes all classes of systems related to early virtual testing for validation of efficiency, resistance, performance, and manufacturability.
Digital Twins	Includes classes of systems related to digital duplication for early control of system performance issues.
Rapid Prototype and Manufacturing Technologies	RTP + RMT: Includes classes of systems related to additive processes, such as rapid prototyping and rapid manufacturing.
Assisted Manufacturing	Includes systems supporting construction and/or direct manufacturing, including new materials and nanotechnology.
Intelligent Assistants	Includes systems supporting the consultation of construction and/or manufacturing data for decision-making (without natural language AI).



Performance	Includes systems related to n-dimensional controls (more than the 3 basic dimensions, or 3D) of design.
Standardization	Includes international design standardization systems, such as standards, good practice rules, seals, certifications, among others.

Source: Prepared by the authors

A digital integration approach has also been developed over the years and is represented by ubiquitous sensor, recording, and communication systems. Dalenogare (2018) describes this integration between information and manufacturing as Cyber-Physical Systems (CPS), which embody the main references to the digitalization of our time, such as the Internet of Things (IoT), 5G systems, Industry 4.0, among others. In other words, the project scenario is fully immersed in digital support, with almost all systems using AI-based routines.

Table 03 – Definitions of the Cyber-Physical digital technology class.

Cyber-physical type	Descriptions
DPSS – Digital Product-Service Systems	Incorporation of digital services into products based on Internet of Things (IoT) platforms, embedded sensors, processors, and software that enable new capabilities.
Integrated Engineering Systems	Integration of IT support systems for the exchange of information in product development and manufacturing.
Big Data	Includes the collection and analysis of large volumes of data, applied in predictive analytics, data mining, and statistical analysis.
Sensor Automation	Automation systems with embedded sensor technology for monitoring through data collection.
Flexible Production Lines	Digital automation with sensors in manufacturing processes, enabling integration with the industrial environment.

Source: Prepared by the authors

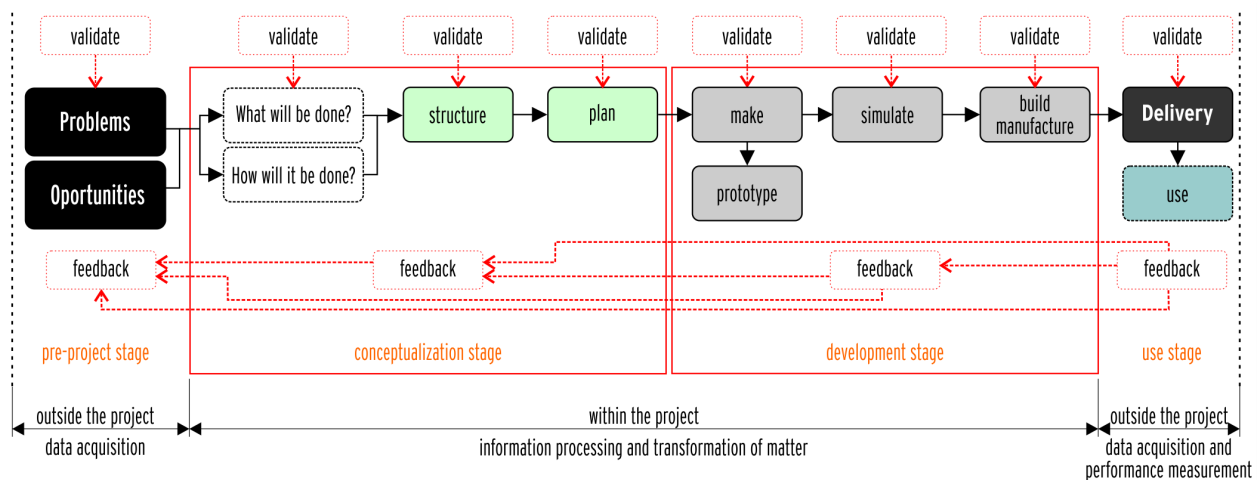
Descriptions of the Cyber-Physical types are presented in Table 03 above.



7. THE APPLICABILITY OF AIS IN DESIGN STAGES

A phased project necessarily defines a sense of development flow, in which four stages are identified: a) pre-project, where project triggers operate; b) conceptualization, where definitions, structuring, planning, and validations occur; c) development, where systems, services, or artifacts are simulated, built, and manufactured; and d) utilization, where the system, service, or artifact is delivered and begins to be used. Figure 3 represents the described project structure:

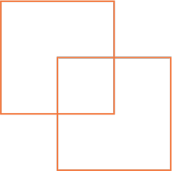
Figure 03 – Project structure and timing of its stages.



Source: Created by the authors.

Stages identified as "outside the project" are characterized by direct dependence on world analysis and can be affected by random phenomena and events, making them more difficult to automate. "Conceptualization" and "development" stages are characterized by constant automation and support for design and production, making them easier to automate.

Denning (2019) explains that computers are ideal for performing tasks that can be organized by routines, such as those involving calculations and well-defined rules, such as "shaping a metal tube." On the other hand, problems with poorly defined routines, such as "getting comfortable," are more difficult to automate. However, common to all project stages is the requirement for validation to advance to the next stage and feedback for correction and optimization of previous



stages. Regardless of the stage, validations and feedback address the search for project-related reality through data acquisition (measurements and/or inheritance), information processing (calculations, mapping, and modeling), material transformations (prototyping, fabrication, and construction), and performance monitoring (performance records). The vast majority of AIs developed to date operate in these processes in a specialized manner, specifically, well-connected blocks.

8. THE AI MODEL ADOPTION LAYER IN THE PROJECT FRAMEWORK

Projects rely more and more on increasingly specialized systems with specific functionality, yet capable of being integrated with other expert systems. Therefore, it is crucial to understand the overlapping layers of digital technology, cyber-physical systems, and AI models. For each of these layers, we have defined specific algorithms, systems, and artifacts.

We know that AI models are being used extensively across all available digital technology. However, these systems use algorithms based on Artificial Narrow Intelligence (ANI) due to the basic need for 100% specialized applications to solve problems across project phases. Figure 4 presents the framework for the project phase structure with the addition of the specialized AI layer.

Based on the initial framework represented in Figure 4, we can consider a current scenario for designers' performance in light of new design practices supported by AI systems:

- Specific Artificial Intelligence base; closed
- No semantic assignment,
- Composed and supported by specialized Narrow AI systems, and
- Organized in perfectly integrated layers (for algorithms, services, and products)
- Need for specific learning and training for AECD designers (including learning codes and programming languages is recommended)

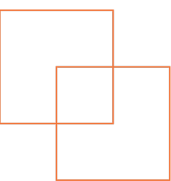
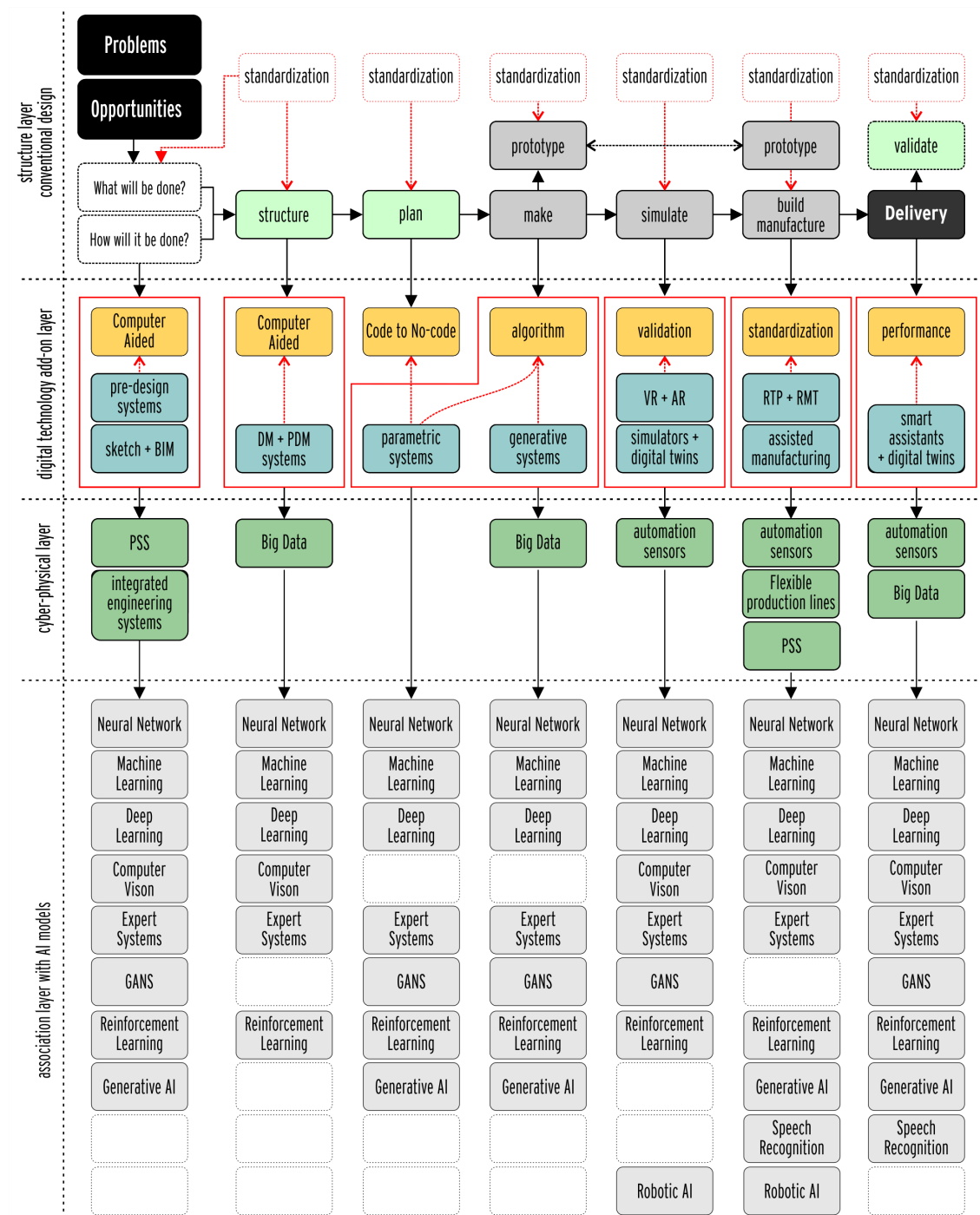
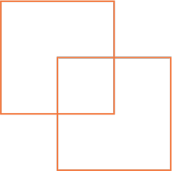


Figure 04 – Project structure with the AI model layer.





Source: Created by the authors.

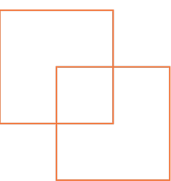
Note that the current and most famous AI model, the LLM model represented by ChatGPT and other derived generative applications, is not directly structured within the application layers focused on AECD. That is, open natural language models are positioned in the outer layers for use in AECD projects, with only indirect interventions recommended, without affecting validated technical decisions. Raji (2022) states that the functionality of this model is currently excessively focused on gaining the trust of ordinary users in creation activities without validation (many design projects go through this process).

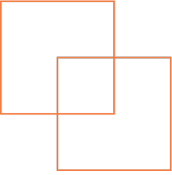
This framing places the entire onus on people (users) to trust AI systems, rather than on institutions to make their AI models more trustworthy. This behavior objectively fails to serve AECD projects.

9. FINAL CONSIDERATIONS

Design processes have undergone significant changes throughout the evolution of digital technologies. The evolutionary maps and framework presented here help understand and validate the above proposition and help identify the scope of action and the level of proficiency required of the stakeholders involved in new projects. They also draw the attention of AECD designers to which class or type of technology should be incorporated into their practices and learning plans. Providing representation and visualization to these AECD project structures, increasingly dependent on assistive systems and AI, is also important, as it allows for the observation of the boundaries of the systems in which AECD projects will be developed.

The positive aspect is that most AI used in AECD projects is based on machine learning, trained by human experts to perform very narrow and specific tasks. The availability, training, and best practice recommendations for the applied use of specialized AIs clearly exist in AECD projects, providing a systemic openness, without excluding the analysis of inherent complexity, to solve problems of conceptualization, explainability, interpretation, functionality, and performance





of algorithm-assisted projects, especially those based on AI. However, it is important to consider that generative AIs based on massive amounts of data/information have not yet proven to be readily apt and functional to solve AECD.

The important thing to bear in mind is that AI will always be a tool, perhaps the most powerful ever created by humankind, but it is a tool. Today, learning to use AI-based design assistance systems is imperative for AECD stakeholders.

BIBLIOGRAPHIC REFERENCES

BARBOSA, Xênia de Castro e BEZERRA, Ruth Ferreira - Breve introdução à história da Inteligência Artificial, Revista de História e Humanidades Jamaxi, v. 4, n. 2, UFAC. 2020

DALENOGARE, Lucas, BENITEZA, Guilherme, AYALAB, Néstor e FRANKA, Alejandro - The expected contribution of Industry 4.0 technologies for industrial performance. International Journal of Production Economics 204. Elsevier, 2018

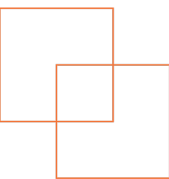
DENNING, Peter J. - Computational Thinking in Science: The computer revolution has profoundly affected how we think about science, experimentation, and research. The Scientific Research Society. USA. 2017

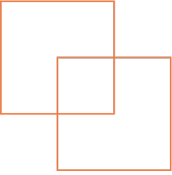
GOODFELLOW, Ian, BENGIO, Yoshua e COURVILLE, Aaron - Deep Learning. Disponível em www.deeplearningbook.org. 2015

HAN, Byung-Chul. Sociedade do Cansaço; tradução de Enio Paulo Giachini. 2ª edição ampliada – Petrópolis, RJ: Vozes, 2017.

KELLY, Kelvin - Inevitável: as 12 forças tecnológicas que mudarão o nosso mundo. Tradução de Cristina Yamagami. HSM, São Paulo, Brasil. 2017

KISSINGER, Henry, Schmidt, Eric e Hutternlocher, Daniel - The Age of AI - And Our Human Future. John Murray Publishers, London, UK. 2021.





LUDEMIR, Teresa - Inteligência Artificial e Aprendizado de Máquina: estado atual e tendências. Estudos Avançados 35, Scielo Brasil, 2021.

MIELKE, Sam - In the Age of AI: How AI and Emerging Technologies Are Disrupting Industries, Lives, and the Future of Work. New Degree Press, ISBN 978-1-63730-434-1, 2021

PINEAU, Joelle, VICENTE-LAMARRE, Phillipe, SINHA, Koustuv, BEYGELZIMER, Alina, LARIVIÈRE, Vincent, BUC, Florence d'Alché, FOX, Emily and LAROCHELLE, Hugo - Improving reproducibility in machine learning research: a report from the NerIPS 2019 reproducibility program. Journal of Machinery Learning Research 22. 2021

PRUNKL, Carina and WITTESTONE, Jess - Beyond near-and long-term: Towards a clearer account of research priorities in AI ethics and society. In Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society. 138–143. 2020

RAJI, Inioluwa, HOROWITZ, Aaron, KUMAR, Elizabeth and SELBST, Andrew. The Fallacy of AI Functionality. ACM ISBN 978-1-4503-9352-2/2/06. USA. 2022.

RAGHAVAN, Manish, BAROCAS, Solon, KLEINBERG, Jon and LEVY, Karen - Mitigating bias in algorithmic hiring: Evaluating claims and practices. In Proceedings of the 2020 conference on fairness, accountability, and transparency. 469–481. 2020

SCOTT, Kevin and SHAW, Greg. O futuro da Inteligência Artificial: de ameaça a recurso. Tradução André Fontenelle, Harper Collins, Rio de Janeiro, Brasil. 2023

TRIMBER - Unwavering integrity in an increasingly complex digital continuum: The Changing Role of the Surveyor. From GIM International - Geospatial Blog Articles. 2023

THOMSETT, Michael C. - The little black book of project management — 3rd ed. AMACOM Books, New York, USA. 2010

