What if AI Apprentices Outperform Their Human Counterparts?

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The focus of this study is to draw a vision of how computer aided architecture may now evolve into artificial intelligence aided architecture (AIAA). Architects have been augmented by computers in the last decades. Therefore, the vision of such an architecture is depicted in correspondence with the ages of human evolution. Implicit knowledge of architecture is therefore explored in connection with the hierarchy of data/information/knowledge and wisdom. Therefore, the conceptual levels of AI as the narrow AI, general AI and superintelligent AI are introduced to the reader in the context of defining the current state and the possible future of AI applications. The narrow AI applications are independently worked at several different domains. This work introduces a hypothetical architect AI that learns all the knowledge of architecture during the knowledge age and later links itself to Artificial General Intelligence (AGI) in the wisdom age. An emphasis is put on occupant centric approach that architects should take on if they would want to train their future apprentices for the best and customized space creation practices. Within this context the design outcomes which are produced by AI are discussed in terms of whether they may still be considered “design”.

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Yapay Zeka Çırakları İnsan Emsallerinden Daha İyi Performans Gösterirlerse?

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Bu çalışmanın odak noktası, mimarinin bilgi tabanı bir yapay zekaya teslim edildiğinde bilgisayar destekli mimarinin artık yapay zeka destekli mimariye (AIAA) nasıl dönüşebileceğine dair bir vizyon çizmektir. Bu nedenle böyle bir mimarinin vizyonu, insanın evriminin çağlarına uygun olarak tasvir edilmiştir. Bu nedenle, mimarlığın örtük bilgisi, veri / bilgi / bilgi birikimi ve bilgelik hiyerarşisi ile bağlantılı olarak incelenmektedir. Bu nedenle, AI uygulamalarının mevcut durumunu ve olası geleceğini tanımlama bağlamında, yapay dar zekâ (YDZ), yapay genel zekâ (YGZ) ve yapay süper zekâ (YSZ)olarak kavramsal seviyeleri okuyucuya tanıtılmaktadır. Dar yapay zeka uygulamaları, farklı alanlarda birbirinden bağımsız olarak çalışılmaktadır. Bu çalışma, bilgi çağında mimarlığın tüm bilgisini öğrenen ve daha sonra kendisini bilgelik çağında YGZ'ye bağlayan varsayımsal bir mimar yapay zekayı okuyucuya sunulmaktadır. Mimarların, gelecekteki çıraklarını en iyi ve özelleştirilmiş mekanları yaratma uygulamaları için eğitmek istiyorlarsa üstlenmeleri gereken, kullanıcı odaklı yaklaşıma vurgu yapılmaktadır. Bu bağlamda, yapay zeka ile üretilen çıktıların, hala "tasarım" olarak kabul edilip edilemeyeği tartışılmaktadır.

Anahtar Kelimeler: Yapay Zeka, Yapay Genel Zeka, Yapay Zeka Destekli Mimar, Mimarlık Bilgisi, Kullanıcı Odaklı Tasarım

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1. INTRODUCTION

Digitally mediated design and construction did not simply provide labor-wise assistance for the industry but also evolved into a digital content that allowed for elaboration at several levels of complexity (Mitchell, 2005). Have digitally produced architectural designs revealed a new type of architecture with novel principles or methodology? Have computers changed the built environment through digital architectural design and construction? With these yet-to-be answered questions architectural design computing has been analyzed and modeled in various research work (Mitchell, 1990; Aish, 2003; Cross, 1984).

The primary concern of this work, however, is to explore whether digital architectural design is evolving from computer aided design (CAD) into artificial intelligence aided design (AIAD) as its next step. Following this concern is the next question whether architecture may continue to be a human task when the rapid pace of computational progress is taken into account. The latter question has been explored within the framework of the evolution of architectural knowledge. The standpoint for this framework is based on who handles the tacit knowledge of architecture since its inception. Whether the contemporary mainstream of architectural design is digital design or not is not a primary concern of this research. However, the new generation of digital design specialists called the *digerati (digital literati)* are considered as the contemporary practitioners of today's architecture (Oxman, 2006).

2. WHO IS IN CHARGE OF ARCHITECTURAL DESIGN?

Architectural design is a process consisting of a set of operations such as *definition of the desired objectives*, *production of alternative design solutions* and *evaluation of the expected performances* (Carrara et al., 1994).

Who holds the knowledge of architecture? The answer to this question seems to have changed several times throughout the history of humanity. The framework of viewing the shift of authorship and expertise of architectural design is depicted on a timeline **Table 1** along with a modest future forecast on who will be the next generation of architects in the midst of the century. Architectural designer's identity has changed due to occupants' needs. The nomadic, neolithic, industrial, information, knowledge and the hypothetical wisdom ages are included in the graphic to help define designer's identity based on who the master builders of that age were.

Within this occupant-centric framework the architecture's knowledge shifted from the nature itself to the occupant during the Neolithic age. This knowledge came from the nature that is considered to be the first sheltering institution in nomadic times to the occupant who decided to settle and took on the decision making role for how and where they wanted their shelter to perform. The next main shift was during the industrial age when the architect took over the space-making specialization and seemed to somewhat dictate and or reflect upon where and how life should be enclosed in the built environment. The knowledge of architecture until this time was created by purely biological intelligence.

Table 1: Architectural designers' identity through ages. Developed by the author.

Architectural Designers' Identity Through Ages		Nomadic Age	Neolithic Age	Industrial Age	Information Age	Knowledge Age	Wisdom Age
WHAT		Huge Areas, Caves	Settlements Social Buildings & Houses for Extended Families &	Cities Industrial, Social buildings Transportation hubs, Homes(Houses, Apartments etc.)	Cities Physical Space, Virtual Space	Homes, Blended Cities Mixed-Reality Space	Galactic Settlements, Interplanetary Portation Space
HOW		Carving	Masonry Stone, Mud Brick	Steam Engines Electrical Machines Iron, Steel & Glass Regulations	File-to-Factory, Construction Robots,Computer Regulations	File-to-Site, Digital twins, 3D Printers, Construction Robots Compliance Automation	Nanotechnology Programmable Matter,Microscopic / Nanoscopic drones
WHO	OCCUPANT	Hunter Gatherer	Agriculturer	Ruler & Worker	Ruler &Worker &Avatar	Ruler &Worker &Avatar	Avatar
	DESIGNER	**Nature**	**The Occupant**	**The Architect**	**Computer Aided Architect**	**AI Aided Architect**	**The Avatar Occupant**
WHEN		200,000BC	10,000BC- 18th Century	1760 1870	1960s	2000	
		Biological			Hybrid		Non-Biological
		Intelligence					

However, 1960s brought a whole new paradigm of the augmented architect thus creating a hybrid form of intelligence between the biological and the non-biological (Kurzweil, 2006). The shift revealed itself in the way architectural design was produced. The computers took on the role of enablers in cases requiring complex computational tasks, visualizations, and representations.

2.1. The Augmented Architect

Looking back at the periods until seventeenth century there was little distinction between professions and disciplines, or between architects and mathematicians (Williams and Ostwald, 2015) the master builders were still expected to master at several other disciplines. However, the eighteenth century witnessed gradual separation of professions from disciplines while the guilds and technical colleges began to emerge. Therefore, architecture began to distance from mathematics due to increased specialization. To emphasize, this distancing was the gradual result of practical moves for vocational and educational institutions educating the next generations. While specialization brought about deeper knowledge to both areas, engineering practices embraced technical and mathematical aspects and architecture gravitated towards being a profession of a comparably wider base of tacit knowledge by the twentieth century. However, with mathematical thinking models architects could clarify and/or quantify the underlying mechanisms of design making the processes more explicit and reaching optimum precision. Nevertheless, the last decades implied an era of gradually growing augmentation of the architects through integration of mathematical improvements (Williams, 2015).

A timeline that a recent research suggests (Chaillou, 2019) four consecutive and interpenetrating periods which distinguishes two levels of creation, in the last decades. The four periods are *Modularity, Computational Design, Parametricism and Artificial Intelligence.* Inventions coming mainly from academic research leading to innovations pave the way to a practice in constant progress. Therefore, Chaillou introduces the age of architectural AI as a culminating point resulting from the spiral feed of the architectural and the computational fields. The timeline starts with *Modularity* pinned to 1930s and lists *Gropius-Baukasten Concept*, *Le Corbusier-Le Modulor('45)*, *Buckminster Fuller-Dymaxion House('46)* and the *Dartmouth Conference-AI('56)* leading to innovations of the same period ending in 1960s. Computational design period therefore witnesses Christopher Alexander- A Pattern Language ('68), N.Negroponte-The Architecture Machine ('70), Architecture Machine Group- Urban II and V. (Chaillou, 2019, p18-19). However, as stated earlier, computation and mathematical presence in architecture dates back to far earlier until the times of stonemasons calculating the topology and geometry of stones etc.

2.2. Computer Aided Architect (CAA)

Architectural design projects no longer have the sole authorship of architects. They require collective decision-making (Eastman, 2008). When the complexity of building projects raised beyond the architects' control, they nestled to their own silos within the industry sharing the workload and responsibility to engineering and construction specialists. Earlier, in the seventies, Eastman et al (1974) suggested a computer database capable of representing buildings, at a scale of construction detail comprising a set of operations, to be developed. This database was envisioned as a probable solution to inefficiencies of building drawings as the principal medium for communication among all parties of building constructions. Consequently, a computer-based description of architectural design was developed. However, there were some problems to be resolved such as hardware configuration, capability to describe geometric complexity of spaces and incorporation of data structures into the generalized database along with many issues unresolved. Looking back, we see that many of the issues that put an end to the computer aided design research is no longer valid. Thanks to the advances in digital technologies both in terms of software and hardware the whole AEC industry earned competitive skills suitable for each step of workflows.

2.3. Artificial Intelligence Aided Architect (AIAA)

Computers and digital technologies provided architecture with immense capabilities implemented in phases from conceptual design to 3D visualization, from design optimization to project management etc. providing architectural knowledge management at unforeseen levels of efficiency. However, those contributions can still be classified as automation of routine tasks for sharing the workload. AI applications however are expected to demonstrate learning capabilities in order to be differentiated from other computational design practices in architecture. *Computers cannot be explained to on how to do specific tasks but if once given the learning algorithm, and the examples to train on they can learn new skills* (Domingos, 2015).

Therefore, AI in architecture has mainly been yielding learning outcomes in the 1980's when models of artificial neural networks appeared in the research field. Rather than a symbolist approach it acquired the processes of human nervous system and the brain as a model. This approach called *artificial neural networks (ANN)* gave the computers the ability to learn even in the absence of explicit instructions. Here, it is important to note that this new paradigm also implied that causality might be replaced by pattern recognition and correlations when *machine learning (ML)* is the case.

Applications of AI or ML in architecture currently suffer from several limitations: *1. they require well balanced training sets- not yet easily available in architecture 2. They require large amount of data – datasets do not exist, or they are immature 3. They lack explainability* (Belém, 2019). However, through the explosion of research in this yet to be explored domain architects are receiving a new awareness of design that is data driven.

This explosion therefore is happening in both academia and the industry covering both theory and practice. Classification/Prediction Applications use ANNs and cover measuring similarities between architectural designs by different architects (Yoshimura, et al, 2018), analyses of changing styles in centuries (Lee, et al, 2015) or age prediction of buildings from photographs (Zeppelzauer, et al, 2018), and architectural style recognition and prediction (Mathias, 2012; Shalunts G., et al. 2012) Therefore Generative approaches include mainly Generative Adversarial Networks (GANs), a more recent model of ANNs that train and learn on large datasets and generate output. GANs basically resemble a game with two players: the generator and the discriminator. The generator creates samples, and the discriminator determines the sample to guess whether they are real or fake. Success comes from generating samples that are drawn from the same distribution as the training data. The samples however do not exist in the training data but are created by the algorithm (Goodfellow, 2017) Architectural research using GANs (Chaillou, 2019; Huang, 2018; As, 2018; Isola, 2016) explore the generation of completely new design solutions that do not exist in the training data containing floor plans and or relational graphs. Thus, advanced design systems can be trained on style and manner based on previous projects. As the researcher concludes, function does not merely represent the topological and geometric knowledge but holds the *latent utility of spaces waiting to be deciphered* (As, et al, 2018). These research studies reveal interesting and productive results for architects helping them search through and find seemingly endless number of design options. However, the architects also witness computers do what they have been trained on for years before they were licensed to practice.

So, it is time if not late to focus on the core value that architects hold which cannot be replicated by AI, if there is any. Cudzik and Radziszewski (2018) tackling this shift of knowledge have optimistic views in the sense that architectural expertise will continue to belong to themselves. However, they claim that architect's role will not change as the final decision maker, basing the argument on ever-changing needs of the society to be solved as the design problem. Another platform based on AI applications is XKool that might refute this optimism. XKool is an AI design cloud platform designed to handle routine tasks to help the architect focus on human innovation. Implementing the implicit knowledge into the computational intelligence. The platform is set to provide non-experts with the opportunity to create architectural designs (Leach, 2018). This resembles the democratization of design capabilities that have been witnessed recently in several other domains of creativity.

As a result, living in the knowledge age Table1, there is a possibility the AI aided architect may take back the responsibility and the power of expertise previously scattered around the industry and become the only licensee of the architectural expertise. However, creativity should also be handled in a new manner since *if it still exists in the design process, it should be found in constraint definition that generate the range of possible solutions to a problem, and secondly, in developing an effective method of filtering or evaluating them* (Leach, 2018).

As the discussion unfolds, there is another possibility that the AI aided architect may face an existential threat after s/he hands over all the implicit knowledge that had accumulated throughout. That scene may take place when and if AGI is achieved.

3. ARTIFICIAL GENERAL INTELLIGENCE

Levels of artificial intelligence has been hypothesized in **Figure 1,** referring to three main goals of AI. The experiences of the current AI research and implementations still belong to artificial narrow intelligence (ANI), also called weak AI. Therefore, it is a definition of AI models helping solve limited number of tasks (Girasa, 2020). Winning against the human chess champion is an example of weak AI as well as the superiority of AlphaGo against the human counterpart. Although the two winning models have different nature, they are both classified as narrow AI, the latter allowing unforeseen moves in an intuitive game that only humans could master until that milestone. The success was attributed to the deep reinforcement learning method of ANNs.

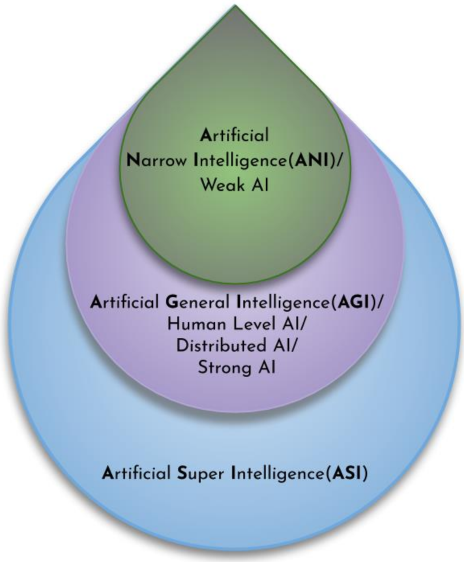

Figure 1: Three Levels of AI. Developed by the author based on Girasa's (2020) definitions.

The field has opponents of the concept of AGI, that artificial intelligence may reach human level also called the *strong AI* (Dreyfus 1972; Penrose 1989). The main reason for contradiction is that the experience of the body is an important generator of human knowledge and that *expertise* is not suitable for explicit definition. Neither can it be explained by causality. However, upon the advent of artificial neural networks, the field witnessed that this objection went obsolete since the AI models had an option of learning rather than being explicitly programmed therefore were not bound by explicit expert knowledge. Nevertheless, after twenty years Dreyfus still argued that meaning depends on context and since contexts are indeterminate, context dependence cannot be formalized. Context therefore needs a background thus a physical presence in the world to build a frame for meaning (Dreyfus, 1992). Goertzel on the other hand argues that for a mind to understand the world it should frame a context based on simplicity building up a *hierarchical* and *heterarchical* structural interpretation of the world. (Goertzel, 2020) Eventually, this discussion of whether AI will reach the level of human intelligence will find it answer, however this is not only a philosophical or scientific discussion. This is indeed a professional discussion for architects.

Handing Over the Knowledge Base

Can AI learn better than humans? Is design being handed over to a new intelligence and/or a non-biological one? This should bring us back to the core question of who the occupant is and who the architectural designer should be. Architects had always had the mere task of creating the most appropriate built environment for the occupant. Through time, challenges changed but the core responsibility stayed the same.

Even during times when the architect had the godlike impression creating the world around us, the goal of the service was the same. The real lesson of AI according to Neil Leach *might not be how "artificial" AI is, but rather how "artificial" — and fundamentally misguided — was our previous perception of the "genius" of human intelligence* (Leach, 2018).

It is a matter of time whether or not all the applications of narrow AI will start connecting at several different levels of interoperability and merge themselves into a strong AI. But for the time being let us imagine an AI called Archiye, being a very hard-working, curious, quick, and diligent apprentice in architecture. Archiye is the next generation of *ArchiRobie* that is the version 1.0 of an AI architect who has started his design journey as an apprentice and achieved his license to design and build urban spaces just recently. *ArchiRobie* has followed the model suggested by John McCarthy (1955) who used the human brain for machine logic. Archiye has just learned that machinery in the industrial age has achieved efficiency through mass-production based on repetition, and economies of scale and that in the information age, digitally controlled machines have allowed mass-customization. She therefore doesn't need to produce any construction documents since she already designed (?!) and produced the *digital twins* of 200,000,000 buildings and the robot counterparts have already started the excavation while parts and raw materials are being transferred to the sites from the most optimal locations to the sites. By this time Archiye already trained itself on modelling how each *micro- drone brick* should transfer itself and connect with which others at what instance during post-occupancy. The following day she will finish training on retrofitting and will evaluate herself to give feedback on what new knowledge she should be learning if there is any left.

Why do we look at AI while we already have the capability to design? Because computers deliver reliable and precise outcomes and most importantly, they are objectively controllable except for the case of black boxes. While AI is augmenting architects, it has the capacity to build up a knowledge base for architecture. This knowledge may scale up thanks to the hardware capacity to run non-stop at huge speeds. Consequently, the AI that has reached and learned all the explicit and implicit knowledge that is present acquires a wisdom of creating the best architectural solutions for occupants whoever they will be in the wisdom age.

4. CONCLUSION

This study sets out to draw a vision of architects being augmented by other disciplines and specializations. The approach of architects to their own area of expertise throughout the ages of nomadic, neolithic, industrial, information, knowledge and the hypothetical wisdom age are discussed within the context of architectural identity. The conceptual levels of AI as the narrow AI, general AI and superintelligent AI are introduced. Design within the context of AI augmented architecture is discussed. A hypothetical AI apprentice of architecture, Archiye, is depicted in order to encourage the reader to tackle the important design and knowledge issues of the profession.

Several questions are raised for today's architects as a modest call to start a discussion by introducing a hypothetical AI counterpart called Archiye that is the V2.0 of the again hypothetical and previously licenced AI architect called ArchiRobie. The resulting implication is that architects might be bound to revise the core reason for their existence within the coming decade. Nonetheless, architects need to redefine their own role and identity either to maintain or transform their profession even after architecture's knowledge base is handed over to an AI.

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