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ScienceDirect

Procedia Computer Science 270 (2025) 1195–1204

Procedia Computer Science

www.elsevier.com/locate/procedia

29th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2025)

AI as a Tool for Untangling Urban Complexities

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Abstract

Cities are among the most complex creations of humanity and urban planning has been utilizing digital toolsets to deal with complexities of urban life for decades. Until now, most digital tools had to resort to single domain and/or declarative/deterministic approaches in analyzing urban systems and were not able to grasp a more integrated view. With the advent of more sophisticated (connectionist) AI-based toolsets, we can dive deeper into untangling the complicated, surprising, and often contradictory factors that constitute urban systems. By utilizing approaches such as GANs, computers might become able to mimic creative problem-solving and visioneering capabilities of urban planners. However, despite the hype surrounding new AI- based tools, they are often more of an improvement of existing technologies instead of substantial technological innovations, and thus need to be assessed by planners critically. The paper sets the usage of novel AI tools into the context of urban planning and discusses how urban planners and designers can interact with emerging AI technologies e.g., through Prompt Engineering. It presents a framework for the coordination and orchestration of human and artificial creativity in the processes of investigating and planning complex urban systems.

Keywords: Urban complexity, Human-AI interaction, Co-creation, Design, Prompt Engineering

1. Introduction: The Complexity of Cities - a call for co-creation with AI?

Few fields are as suitable for AI application as urban development, urban planning, or urban design. Even the most capable human intelligence and creativity reaches its limits when facing urban complexities. Comprehending the multiplicity of intermingled urban systems easily surpasses human´s cognitive and creative capacities [1]. For urban planning and design the growing powers of algorithmic analysis and synthesis provide promising avenues for urban research and professional practice [2, 56, 57]. On the background of the swift evolution of analytic and

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10.1016/j.procs.2025.09.240

creative AI, a closer look at urban complexity can illuminate the potentials and limits of new "creative superpowers" like Generative Adversarial Networks (GAN) in this context.

The complexity of cities increases by several key drivers. Commonly, urban planning and development deals with many objects, actors, and challenges. With most urban agglomerations continuously growing, the number of relevant system components (people, vehicles, built objects etc.) are increasing, thus increasingly demanding for statistical and data-based approaches. In addition, the respective urban systems are deeply interdependent and dynamic, interacting in ways that are difficult to predict or control. And we must acknowledge that cities are not only technical engineering tasks, but socio-cultural environments that are largely determined by factors like economy, history, aesthetics, security, and identity.

We must view a city therefore as a system of systems that brings together in one place very diverse social communities, buildings and infrastructures, energy and mobility networks, public and private institutions, regulations, and legal codes [3]. Each of these systems – independent from the other systems – functions along its own logic of operation and development. Their individual system rationalities ("Eigenlogiken") determine to a large degree how they will evolve in the future, thus imposing certain path dependencies. In effect, urban planning and development deals with multiple intermingled systems synchronized or harmonized only to a limited degree. Usually, they were not created from conceptual unity – from a comprehensive masterplan or integrated holistic vision – but have unfolded over time, thus bearing substantial centrifugal momentum [4]. Further complexity adds when we take into consideration that each subsystem is quickly transforming. Not unlike living organisms, they own metabolisms and continuously change shape and structure. As the scientific term "system dynamics" only vaguely grasps the level of complexity that distinguishes urban systems, alternative approaches and models are needed.

While real-time urban management attempts to monitor and control the dynamics of urban systems in their present state and near time future, an evidence-based long-term city planning and construction appears to be improbable, on a level perhaps comparable to "weather design" (which, however, has been attempted already). Due to their inherent complexity, the reliable anticipation of future urban structures, shapes and processes remains highly uncertain in the longer temporal perspective. The multiple interwoven urban systems contradict rigid determinism, rendering the purposeful planning and design of cities ever more a *contradiction in adjecto*. Trying to face these conceptual and cognitive challenges, a new science of cities has emerged over the past half a century that replaces planning and design approaches with statistical methods, computational simulation, and data-based modelling [1]. Nonetheless, there remains a strong sociopolitical urge to reliably anticipate cities. Given, that ultimate planning schemes ("positive design") may be not possible, it remains a central task for urbanists to ensure that no disadvantageous schemes will be put in place. Trying to anticipate and avoid harmful solutions, for such a "negative design" the term "collision planning" has established itself in architecture and engineering. But what are the corresponding means that we can use for such the same end in urbanism?

It is surprising how limited the analytic and creative instruments have been that were used over centuries for urban planning. Despite the complexity of urban spaces, relevant planning tasks have been pursued with simple mass models, drawing visualizations, figure ground plans etc. as the conventional tools of urban planning. While the array of these instruments forms a comprehensive analytic and synthetic apparatus when properly used, the means and media remain separate and disintegrated. Whether a planner manages to grasp with them existing urban complexity, depends on an elaborated process of their application, and the deep knowledge, talent, and experience of their user.
To comprehend complex phenomena, adequately complex instruments are required (simple scales will not measure subtle phenomena). As the subject matter "city" unfolds on high levels of complexity, the planning of which raises a justified demand for a descriptive and generative apparatus whose structure needs to mirror that complexity – in cognitive, creative, and operational terms. This is the point where the capacities of artificial intelligence and artificial creativity come into play as potential new instruments for urban design and planning. Their built-in levels of algorithmic, structural, and cognitive complexity may be responsive to the complexity of urban phenomena and challenges.

2. Complexity in Urban Planning Practices – Towards Digitalization

The high level of urban complexity has been a focal interest of researchers at least since the 1970s, who utilized systems thinking and other systems theory-based approaches to understand and describe urban environments. Especially early attempts tried to understand cities as a kind of computational machinery that works in a logical and coherent way. With time, it became clear that the complexity does not solely result from the sheer number of elements and interactions – which may be computed by sufficiently powerful computer sooner or later – but also their often-contradictory relationship and the fuzzy nature of boundaries between subsystems, systems, and the environment. Cities can hardly be described in a rational, or top-down approach, as such one fails to grasp the human origins of cities [5]. Urban systems are built from the bottom-up. Even though humans create organizations and institutions, form collectives and groups (often in a mixture with top-down forces), the decisions that constitute urban life are still made on an individual level. This might also explain why urban planners deal so often with "wicked" problems which do not have any objectively correct solutions, and in which every intervention can have unexpected effects on other elements of the same system [6]. Planners can hardly foresee the scale or scope of the (side-)effects of their interventions in such complex constellations.

Along with the realization that urban systems cannot be understood in a top-down and supposedly rational approach, planners also understood that their expert knowledge is in most cases not comprehensive or specific enough to come up with ideal solutions in planning processes. Instead, they rather act as mediators in the multiplicity of people, institutions, opinions, or demands involved. A standardization of planning processes can be achieved only to a very limited extent.

Healey [7] identified the communicative turn in planning, which understands its subject as a communicative process. Here the aim is not to come up with rational or seemingly objective plans from a god's-eye view but to discuss and envision alternatives and try to reach a consensus among the involved parties. Between them, information and expertise are shared, while citizens appear in these processes also as experts, as they know local conditions best and can provide valuable feedback to planners. The focus lies here on the exchange of thoughts and iterative approaches, instead of a solely technical understanding of the city and planning interventions.

On such background, digital culture unfolds an increasing impact on architectural and urbanist thinking as well as on their practices. Schönwandt [8] offers a new perspective when he localizes planners in the so called "everyday world". In contrast to their previous self-understanding as being detached from the systems they plan or manage, here planners are viewed as integrated part of societal trends, transformations, and influences. Planners´ thought and practice relate to, and are conditioned by, existing or emerging technologies, and they are prone to misconceptions or misjudgments, like everybody else. The fact that planners have expressed specific expectations for new technologies and experiences over the past decades indicate that they are not unaffected by societal hypes or new technological trends. This is evidenced, for example, by the hype surrounding new digital tools in data acquisition, analysis, visualization, and dissemination. Another example are "smart cities" and regions that popped up around the globe in the late 2000s, trying to incorporate concepts such as ubiquitous connectivity and ubiquitous computing, in many cases relying on a perceived self-explanatory nature of data by itself [9]. "Smart City"-approaches have been criticized by a variety of authors in the meantime [10; 11], while many "Smart City" initiatives such as the Toronto Waterfront [12] did not find success.

The shortcomings of these approaches often are not in the technologies themselves, but in the anticipations that they will provide universal, easy-to-access solutions to a broad variety of urban problems. Many smart city critics [9; 13; 14] have pointed out that digital tools are valuable assets in the toolbox of urban planners, however, they must be applied in accordance with the specific context, while recognizing their potentials and limitations. Existing digital tools in urban planning are not yet providing a comprehensive, real-time, and real word understanding of cities. This is not just due to issues of data availability or to computational limits, but to their reliance on deterministic logics that falls short of capturing the ambiguity and unpredictability of urban reality. Emerging AI tools, however, promise a shift towards more associative (and less deterministic) approaches; they may be better suited to modeling the complex, bottom-up nature of urban systems.

3. Understanding the Logic of AI

The thriving term Big Data – which ruled much of the technology discourses in the 2010's – has been replaced in the last years by Artificial Intelligence [15] as the major buzzword both in the public and the private sphere. The term itself looks back to a decades-long history since its inception in the 1950s. The relation between humans and AI, along with the thinking/problem solving capabilities of computers, have been intensively debated since then [16]. In the early 2020's we saw AI leaving its initial field of computational science [17] and conquering tasks that have been initially deemed to be suitable solely for humans. Good examples are widely accessible prompt-based content generation algorithms [18] for images, for texts, or audio [19]. These algorithms are not only able to generate sophisticated outputs mimicking human creativity and communication patterns but are also being adopted in larger-scale digital ecosystems [20], potentially redefining how humans will interact with computers soon. Humankind is clearly on the way towards ubiquitous computing [21] and AI-human interactions will become an integral part of our everyday lives (and world - in reference to Schöndwandt), influencing among others how we view and plan our cities. As computers become steadily more sophisticated in their way of communicating with humans, the distinction between human-specific and computer-specific communication becomes fuzzier.

In the field of human-computer interaction (HCI), we are on the move from rational to design approaches, a distinction coined by Winograd [22]. Here, the rational approach focuses on explicit descriptions of the content or tasks the computer deals with, while design approaches can include human ambiguity (e.g., chatbots that deal with natural language, or image generators that use natural language prompts to create visual outputs). How AI works in the back end can also be divided into the two approaches: a symbolic versus a connectionist one [16]. Symbolic AI builds up on the explicit definition of formal rules and rules, while connectionist AI lacks these completely. Symbolic AI is more centralized in both organization and computing, while connectionist AI focuses more on networks and parallel information processing.

This contrast is especially relevant in urban planning, because – as argued in the second chapter – urban complexity cannot be grasped by explicit and rational definitions of urban elements; the whole (city) is more than the sum of its parts [1]. The application of connectionist approaches in architecture has led to evolutionary computing being applied in conceptual design [23], however, the same logic can be transferred also to more advanced simulations that in principle can depict the (bottom-up) constitution of a given system by the help of agent populations [24, 56, 57]. This might suggest that the constraints in representing urban complexity pointed out by Batty (2020) could be overcome, but only if we disregard a shortcoming of connectionist AI, a certain the lack of understanding of the (computational) processes running behind their application. Connectionist AI are generally unable to understand whether observed (and learned) phenomena result from correlation or causation. This mirrors debates from the late 2000’s about the question, whether advances in computing can let the data speak for itself without accounting for the underlying causal relationships between elements of the analyzed system. In the field of urban planning, this leads to the re-assessment of the question on whether we are moving towards a data-informed or a data-driven urbanism, as defined by Kitchin [9].

Some critics point out that the term AI is a contradiction [17], arguing that AI is “neither artificial nor intelligent”, while Bishop [25]) calls it plainly “stupid” for the lack of understanding capabilities. While we can apply AI to capture extensive pictures of urban systems, the lack of insight into these processes makes it unlikely to fully capture all the constituting elements, connections, and interactions.

Nevertheless, AI-based approaches have their place among the toolsets of urban planners, implying a tradeoff between the more integrated (connectionist) but obscure approaches on the one hand, and the transparent (symbolic) yet more limited approaches on the other. Current discourses on the relationship between AI and urban planning (e.g., based on Digital Twins) are highlighting these questions, but the focus of research lies more on building design or architecture. Mrosla and Both [26] list the subareas of “robotics, pattern analysis, pattern recognition, prediction and knowledge-based systems” as the fields of AI that have potentially the strongest implications on architecture. Apart from robotics, these fields are also the ones where we can recognize a relevance to urban planning – many of them have already found their way into problem solving related to urban complexity. Examples cover a broad variety of analyzed subjects, such as discourses in social media [27], time-activity trajectories [28], land-use recognition [29], but also modelling land-cover and land-use changes [30]. These represent already well-applied methods for an – at least partial – understanding of urban complexity. Common to them is the utilization of stochastic approaches, such as Markov chains.

It is, however, important to highlight that these are in principle symbolic AI-approaches, in which the computer builds a model capable of recognizing and applying the distributions of proportions between different states [31]. This means, these methods can depict certain aspects of urban life to a varying degree of reliability and validity but are constrained in dealing with unpredictable processes, such as disruption or innovation, which are still key characteristics of urban life [32].

A further prominent application field of AI in urban planning lies in synthetic data generation. As discussed in the examples above, modelling and simulation approaches can be exploited in a broad variety of fields; their applicability, however, is often constrained by challenges of data security, privacy, costs, management issues, accuracy of representation, or data quality [33, 34, 35, 36]. Therefore, obtaining the suitable training data for machine learning algorithms can be difficult. This applies especially for architectural or urban pre-design stages, when design decisions are not yet consolidated, and buildings or neighborhood not built yet. Therefore, actual training data might be unavailable or unsuitable. Additionally, in many cases privacy issues also hinder the obtaining of required datasets in the required scale or generality. Under such conditions, synthetic data generation is a promising approach particularly in the pre-design stage of urban planning. With them, planners and designers can overcome the challenge of non-existing (or not-yet-existing) datasets when they want to anticipate not only the future image of a new neighborhood, but also the needs and demands of its future inhabitants and users. Synthetic data can help identify issues and design possibilities and contribute to planning processes to match the specific requirements of the parties involved [56, 57]. Simulations based on synthetic data allow the prototyping of solutions and services without utilizing actual data – an approach recently investigated in various scientific fields, such as public health, logistics, business innovation, finance, management, and sustainability [37].

The emergence of more advanced (connectionist) AI methods in urban planning is mainly related to Artificial Neural Networks (ANNs). ANNs work with more complexity with multiple layers of analysis and parameters that can adapt based on the data applied to the network and are also able to incorporate non-linear regression [38] in contrast to Markov chains. ANNs, Deep Learning, and related methods are suitable to handle larger and more complex urban datasets [39] and have been used to model and simulate topics such as traffic management [40], ecological sustainability [41], or the effects of town development policies on energy effectiveness [42]. The perhaps most disruptive feature of ANNs and other connectionist approaches, as based on their associative logic [43], lies in their potential to mimic and facilitate human creativity in the design process [44] – a field that had been reserved solely for the human mind for a long time.

4. Prompting Design: Applying AI´s Associative Logic from Text to Image

To investigate the applicability of AI in the creative processes of architecture or urban design, we need to define criteria that these intelligence tools need to fulfil. In general, architectural design and urban planning must effectively meet and converge functional, economic, and aesthetic requirements [45]. Hence, informed design and planning processes are necessary to create well-functioning and well-integrated systems of high socio-technical complexity. We can thus define design and planning quality as the synchronous fulfilment of requirements coming from multiple sides e.g., designers, constructors, owners, or regulatory agencies etc. [46].

AI systems can analyze large data, identify patterns, and use those patterns to generate new content of various types, such as artistic, functional but also structural design [47]. By exploring the now (digitally) available multitude of inspiring objects – be it text or image – as well as a rage of new generative processes, designers can think out of the box and discover innovative forms of expression. As a promising new means for architectural and artistic creativity text-to-image models, for example, enable the language-based generation of complex geometric forms. With easy-to-use text interfaces, planners and architects can quickly generate, variate, and optimize their intended designs. To run such processes efficiently and effectively, however, the proper usage of the generators needs to be learned and trained.

With HCI steadily moving into the field of urban and architectural design, prompt engineering – the targeted phrasing of instructions to be given to generative AI engines – is becoming an important new creative skill. This requires from architectural and urban designers' new analytical capabilities. While this skill learning is still a trial-and-error process in the current stage of content generation algorithms [48], first systematic guidelines are emerging that define key modifiers for prompting, such as: subject terms, image prompts, style modifiers, quality boosters, magic terms, and repetitions.

Subject terms define the context for the generated outcome; style modifiers add a characteristic style; image prompts link to external resources that are added to the textual input prompt; quality boosters increase the artistic qualities. Magic terms introduce an element of randomness to the visual, resulting in an unexpected and surprising outcome, while repetitions emphasize certain factors of the generation process. Further suggestions for prompting emphasize keywords (rather than longer phrases), repeating or iterating the generation process, choosing lower lengths of optimization (i.e., 400 iterations), borrowing artistic styles or manipulating them [48].

As such content generators feature mostly the characteristics of connectionist AI, designers and planners perceive them as “black box” systems. A comprehension of how AI develops output, and which creative paths are taken within the system, is by default constrained. To enhance transparency and turn the black box into a glass box, so-called “Explainable AI” approaches are suggested [49]. Glass box systems provide recommendations to the user, together with beneficial explanations that may influence the user’s decision making. Recent research on” Explainable AI for Designers” targets co-creative approaches with AI/ML technologies [50].

The examples presented in the following section highlight the significance of accurate prompting and show how little changes in the texts can result in large differences in the imagery.

Fig. 1 Comparison of visuals related to prompt modifiers. Prompt 1: ”A very very very beautiful city”; Prompt 2: ”An extremely beautiful city”; Prompt 3: “An extremely beautiful city trending on art station” (Images generated by DiscoDiffusion / HCU Digital City Science)

Figure 1 displays the broad variety of generated images with slight modifications in the prompt, highlighting the significance of modifiers in the prompts. Different outputs appear by repeating the style modifier “very” for the magic term “beautiful”. The usage of a second magic term “trending on art station” gives very different visual output.

A special capacity of AI lies in translating fantastic and hardly imaginable concepts into clear visual representations. As discussed in chapter 3, connectionist AI tools that utilize associative logic are able to mimic human creativity. They can come up with visuals based on terms in prompts that humans would deem difficult to connect in explicit and rational manner. **Figure 2** depicts the imagery of an underwater forest city illuminated by moonlight – a hard to imagine urban setting that neither a human nor a machine designer could model solely by using declarative or deterministic logic.

Fig. 2 AI and imaginative complexity displayed by generating images from the prompt: ”A forest city under the ocean in the moonlight” (Images generated by DiscoDiffusion)

These examples show how prompt engineering will become a central technique of designers and planners. It is a first attempt to address the main challenge in applying connectionist AI tools – the lack of insight during their application. Precise prompt engineering and a careful analysis of the resulting outputs may lead a way towards a comprehension how AI tools develop their outputs, and why and which decisions were taken during the generative process. Through such investigations, urban planners and architects can build up an understanding of the interplay between machines and humans and become versatile orchestrators of their interaction processes.

5. Orchestrating Creative Interaction between Human and AI

AI approaches – especially associative, generative tools – offer us a promising opportunity to cope with the complexities urban planning and architectural design [47; 52, 54, 55, 56, 57]. The purposeful shaping of the co-creative processes with AI emerges as a new skill that planners and designers need to acquire. For this challenge, systematic research should establish reliable guidelines. What is needed on a higher level of HCI, and design methodology is an overall orchestration of the co-design and co-planning process between creative humans and machines [58]. As we may have to deal with a multiplicity of human as well as artificial intelligences (collective creativity, distributed computing etc.), various instances need to be aligned and coordinated in the creative process. Methodologies have been investigated how such a cooperation can be steered as to transforming the black box of AI into a glass box [49,51]. An outline of the co-working and communication processes with AI assistants in urban planning and design tasks needs to consider the different capacities and roles of artificial creativity and human planners. The AI-human interaction design must line out clear operative instructions for both sides in order to achieve the creation of a certain design or planning product. The joint "choreography" is to indicate when and how AI respectively humans should act in the creative process – in which sequence and direction, and with how many iterations. Here, interaction intensity may differ regarding the specific users and the application context. [15].

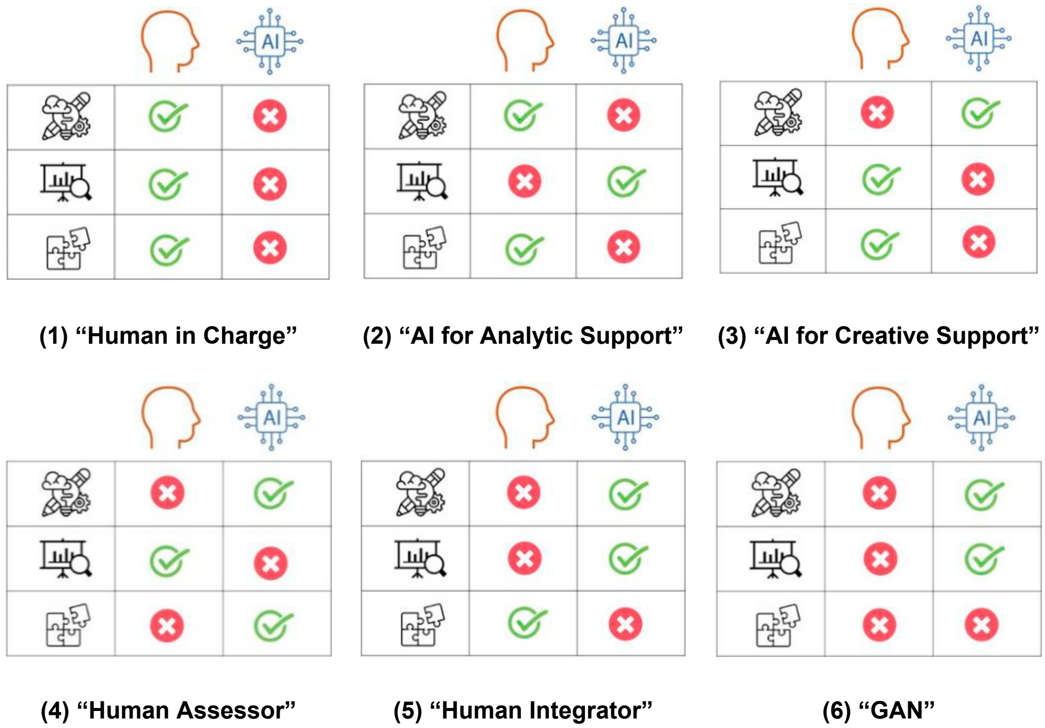

Fig. 3 Cooperative constellations of human and artificial intelligence in the process of design

Figure 3 outlines possible division of work in a co-creative process planning and design process [52]. It shows how the general steps of a creative process – reaching from initial inspiration and idea generation over concept analysis and critical assessment towards synthesis and design integration – can be assigned to either human or machine intelligence, or both. It indicates that various cooperative constellations of human and artificial intelligence exist, as derived from the nature of the specific design or planning tasks. For example, tasks with high social impact may require human assessment throughout the process which, however, may be initiated by a plentiful of impulses generated by an algorithmic inspiration engine [47]. Tasks requiring high technical precision but minimal aesthetic input can be delegated mostly to an AI, with humans focusing on initial vision and task definition.

The presented cooperation schemes, however, do not yet clarify the procedural structure of the human-AI collaboration. To give a clear guideline as to who acts when – whether receiving inputs like images or generating outputs such as design proposals – another notation is needed. One suitable way to orchestrate such processes is the usage of so-called "Swim Lane Diagrams" (**Fig. 4**). Like a music score defining for each player of an orchestra which music sequence he needs to be play at a certain moment, a similar choreography can be established for the co-creative human-AI process, clearly outlining the sequence of required actions taken either by human or machine instances. On the one hand, such scores would enable the otherwise difficult representation and monitoring of creative processes (which often run in iterative sequences of feedback and feedforward loops, and through repeated phases of divergence and convergence)[53]. Thus, the scores would function as a protocol of interaction and bring transparency in procedural terms.

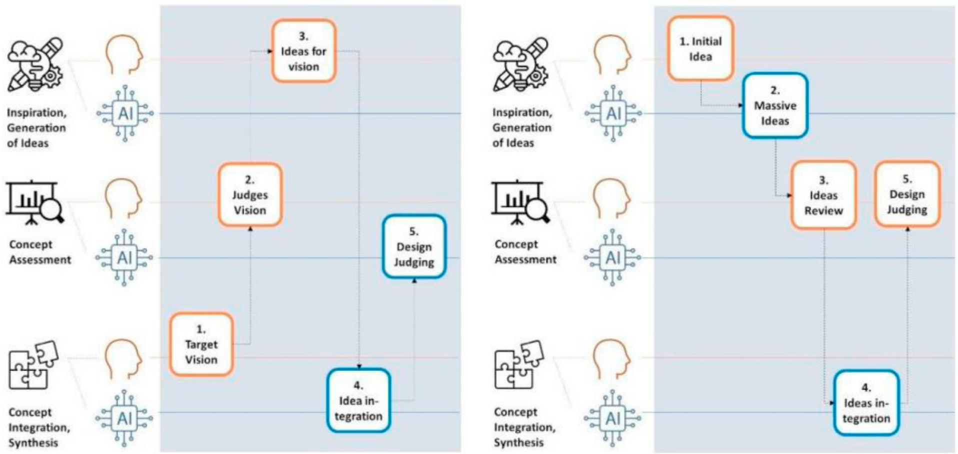

Fig. 4 Swim Lane Choreographies for Human-driven, AI-optimized process (left); Human-AI collaborative relay (right)

On the other hand, these scores enable the systematic investigation and purposeful creation of the collaboration processes that are supposed to unfold between man and machine. Here, the score turns into a creative means itself enabling detailed process design and an assessment of the process quality. Both aspects improve the understanding of the otherwise opaque process of AI-driven creativity, opening – at least to a certain extent – the black box of automated design generators.

6. Conclusion

The application of connectionist and associative AI opens a promising approach for comprehending and shaping urban complexity. The establishment of new forms of human-machine co-creation through AI is a learning process. Planners and designers need to adapt and establish new methods and instruments to become versatile with AI in their fields of practice. Associative AI enables them to rapidly create variations of complex concepts through learned patterns; it can process large amounts of data visually and create inspirational work with unique technical cues. Analytic and symbolic AI, in addition, can add substantial value in the format of assistance systems in the urban context e.g., smart transportation, energy-efficient infrastructure, or risk identification.

In this text, we argued that AI is a very broadly defined term and many techniques branded as such are a logical development of existing technologies and do not necessarily feature a disruptive character. Symbolic AI, where elements and the environment of the analyzed systems need to be defined, have been utilized for decades and have proven to be in many cases useful in planning processes. General advancements in computational powers and capacities allow more fine granulated stochastic analysis tools (based on Markov-Chains) that can be well used especially in analyzing single-domain phenomena, especially in a descriptive, short-term perspective. Synthetic data generation might become an asset in generating training data, that opens up new fields for machine learning algorithms. However, these tools are by their learning principles constrained to the scope of their training data and are unlikely to be able to depict the unpredictability and the complex relations that make up urban systems.

Connectionist AI-tools are technologies that are currently in their early stages. GAN-based designs have been already applied in building designs, facilitating the production of different possible variants, from which human assessors can consequently choose best options. AI-image generators can create images from prompts and envision previously hardly imaginable building designs, constellations, visuals or styles. The field of prompt engineering has a potential to become a key capacity of architects and urban planners, who also need to remain process moderators and coordinators. New approaches in human-machine-interaction are required.

This study highlighted the importance of understanding the nature, logics, potentials, and constraints of respective tools and approaches, sketching a number of specific constellations of humans and computers in the pursuit of specific creative tasks. The presented paper does not aim a general definition of the role of AI in an urban planning process (which is hardly achievable due to the difficulty of standardization) but argues for a better description and understanding of the specific steps needed to orchestrate a meaningful and sensible co-creative process making full use of novel technologies in the domain of planning.

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