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12. Artificial intelligence and post-pandemic recovery

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INTRODUCTION

With the increasing capability of Artificial Intelligence (AI) systems to solve complex problems, AI has become one of the main themes of our life that cuts across various topics. AI algorithms have been used to "optimize" the future and increase the quality of life. One of the prominent features of AI resides in the digitalization of the built environment. Optimizing the built environment to improve quality of life, adapt to climate change and respond to crises requires strategies to redesign, reproduce and manage the traditional ways the built environment has been shaped. Today, the design, production and management of the built environment are confronted by many societal and environmental challenges for which the involvement and participation of citizens, industries and businesses are essential. AI can offer new possibilities around how we can better organize the built environment and more inclusive participation. The Covid-19 pandemic has been a period during which the built environment has been heavily affected. We as academics, practitioners and citizens need to start rethinking about how to manage and operate buildings, the health and safety of occupants and even how certain businesses can continue to function in the case of a health crisis. This questioning has also been supported by big organizations that have called for new ways of thinking and the use of digital data.

For example, during the Covid-19 pandemic, the World Health Organization (WHO) highlighted the role of AI as "a tool to support the fight against the viral pandemic". They argue that AI can serve as an important intervention to overcome health crises while raising awareness and accelerating preparedness due to its ability to respond to collect a vast array of datasets in a short time frame. In the context of the built environment, AI can provide similar means via machine learning, digital twins, robotics and so forth to incorporate real-time data into the design and management of the built environment and transform the built environment in semi-automated platforms digitally. These technologies can bring into sharper foci the need to harness and leverage our buildings' digital infrastructure, data and real-time information. Building owners, operators and users can recover from the external shocks via switching to "smarter operations" which can respond to changes and adapt in the case of health crises as well as other uncertainties. Therefore, addressing Covid-19 has been a key factor of digital transformation within the built environment. In this chapter, we demonstrate how we can use AI for post-pandemic recovery. To do that, we first start by addressing the digital transformation and the role of AI. We then discuss how we can accelerate this transformation within cities. We will reflect on the Covid-19 crisis and the impact of the crisis in the built environment. Then we reflect on what AI can propose for post-pandemic recovery and future research avenues for cities.

DIGITALIZATION AND RESPONSIBLE AI

John McCarthy coined the term Artificial Intelligence (AI) in 1955 to describe "the science and engineering of making intelligent machines." Taking as a starting point the conjecture that every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it (McCarthy et al., 2006), researchers from a diverse set of disciplines got together in the Dartmouth workshop in 1956 to discuss some crucial aspects of the AI problem. Since then, the field of Al has had cycles of success, hopelessness and (misplaced) optimism.

AI algorithms today have become widely accessible and are being used to support many services and sectors (WIPO, 2019). For example, AI provides financial institutions with new mechanisms to fight money laundering (Han et al., 2020), has been extensively applied for image classification in the medical domain (Litjens et al., 2017), and supports automated vehicles to perceive the surrounding environment better and to make motion decisions (Ma et al., 2020). The promised ability of AI systems to enhance productivity, improve forecasting, save resources and increase safety provides many opportunities to improve our lives (Bughin et al., 2017).

Nevertheless, such recent advances, combined with the media hype on highly publicized technical breakthroughs (e.g., AlphaGo winning the game Go against the best human player), put forward the narrative that AI is (or very soon will be) able to outperform humans in most tasks. This perspective, often influenced by science fiction, overlooks many of the flaws in current applications of AI and presents a scenario where such systems can make "optimal" decisions. However, mistakes often do occur and deploying AI algorithms in human-inhabited environments comes with the risk of inappropriate, undesirable or unpredictable consequences (Cavalcante Siebert et al., 2022). Examples of such consequences include fatal accidents with automated vehicles (Serter et al., 2017) or airplanes (Johnston & Harris, 2019), racial discrimination in assessing the risk of recidivism (Angwin et al., 2016) and racial profiling in determining governmental benefits (Amnesty International, 2021). The distributions of the benefits and downsides of the use of AI systems can be very unbalanced and have a significant impact on different stakeholders, from individual users and minority groups to society at large.

Aligning the design and use of intelligent autonomous systems to moral values and societal norms becomes a necessity (Umbrello & De Bellis, 2018). Given the profound impacts these systems can have, this alignment should not be done in isolation from its socio-technical context (Dignum, 2019). No AI system is an island. AI development must take a complex socio-technical system perspective, where users, designers and regulators, among many other stakeholders, interact, shape and are shaped by the AI systems. Responsible AI development requires the informed participation of all stakeholders (Dignum, 2019) throughout its design, use and evaluation.

AI IN THE BUILT ENVIRONMENT

AI has been a hot topic for the built environment, especially in the context of grand societal challenges. In recent years, scholars and practitioners have been working on developing mature and emerging applications for use cases on various scales.

For building and project scales, some of the mature applications include: AI for project cost forecasting so that cost overrun can be prevented in the bidding stage (Moon et al., 2020); AI techniques for the conceptual design stage (Pena et al., 2021) and safety prediction (Baker et al., 2020) during the construction stage; and AI for facility management (Sanzana et al., 2022) in the operation and maintenance stages. Some of the desired or emerging applications include: AI for productivity improvement on construction sites (Onososen & Musonda, 2022); AI and Internet of Things (IoT) combined for robot coordination in prefabricated housing construction (Zhu et al., 2021); and AI for predictive maintenance with human knowledge (Wellsandt et al., 2021).

For other scales, there are also various developed and emerging applications with AI. For example, at the infrastructural and urban scale, AI for road traffic management in combination with IoT (Ouallane et al., 2021); for the material and component level, there are AI algorithms used to detect building materials and components from images (Rashidi et al., 2016). For the city and regional level, there are also AI algorithms to generate large-scale city models from point clouds (Lafarge & Mallet, 2012) and using AI to predict scenarios for resilient urban environment (Li et al., 2022).

What has been seen is that no matter what the scale is, more and more emphasis is being put on the use cases of AI. There is much concern regarding issues like ethics, and privacy problems associated with AI. Therefore, it is essential to further dive into the AI areas not just from the technological development perspective, but also emphasize the connection with people. In the Netherlands, there is a special working group (NLAIc) focusing on four themes of AI in the built environment, including the adoption, standardization, education and acceptance of AI (NLAIc, 2022). We have established an Artificial Intelligence lab (AiBLE) to research the adoption and acceptance of AI in the energy transition and circular transition (two main themes of research due to the grand societal challenges we face). In this lab, we will explore negotiation agents and responsive and responsible human–AI interaction to help decision-making processes during these two transitions with and for stakeholders and suggest behavior changes using reinforcement learning. In this way, we try to reduce the gap between policy goals and practice (AiBLE, 2022).

During the pandemic, more specifically, we have seen the use of AI and Big Data to support people's daily life and physical activities based on scenario forecasting and this could be further explored to link post-pandemic recovery with public-health and stakeholders' needs in the built environment. Some of the potential applications are for example, how to use AI to predict office occupancy in the post-pandemic period (Abdel-Razek et al., 2022) and how to design investment and portfolio management strategies in the real estate sector due to pandemic impacts (Kowalski et al., 2022). During the pandemic, more people began renovating their houses, which creates a lot of construction demolition waste. Arguably, AI can play a significant role in enabling the reuse of these materials to some extent like the façade systems, including but not limited to aluminium, glass, wood and other metal components via material passports and the metadata it provides. There are some examples in the Netherlands that identify possibilities of façade reuse and recycling (PerpetuAL, 2022). In all these cases, the connections with people are via use cases and the technological development can support recovery via improving the resilience of the society facing uncertainties like pandemic and other natural disasters.

AI AND THE BUILT ENVIRONMENT IN THE POST-PANDEMIC RECOVERY

Embedding a new technology such as AI requires an integrated approach due to its multi-scalar engagement in which various stakeholders as well as end users are involved. During the Covid-19 pandemic, a series of global exercises have been witnessed amongst different groups of people and unprecedented levels of global collaboration have been witnessed amongst a series of different services. While healthcare data have been used to inform citizens and public-health decision making, transportation records and personal data from smartphones have been incorporated to track people's movements and help manage the control of the pandemic (Syrowatka et al., 2021). That said, the performance of the application of the AI technologies depends not only on the availability of the data but also on the digital infrastructure supporting the machine learning environment, the interoperability between datasets and the privacy of individuals' data (ibid.). Mobile phones with AI-powered apps and wearable technologies that can harvest location usage and health data can accelerate the decision-making process where such technologies enable patients to receive real-time waiting-time information from their medical providers about their medical condition without them having to visit a hospital in person, and to notify individuals of potential infection hotspots in real time so those areas can be avoided (Petropoulos, 2020).

One of the takeaways from the Covid-19 pandemic has been the importance of data-driven learning that has become crucial for decision making. During the pandemic, a series of non-pharmaceutical interventions were taken by policymakers and governments such as travel bans, business closures, curfews and social distancing. As Syrowatka et al. (2021) argue, many of these decisions have been based on expert recommendations rather than data-driven forecasting. For example, implementing restrictions such as business closures or home stay can reduce the infection-related spread of the virus but also contribute to social isolation and economic decline. At the same time, due to the inequalities of the housing market, the pandemic has reinforced some of the important questions in the built environment in relation to access to public space and the quality of it (Gruis & Ersoy, 2021). Abbs and Marshall (2020) point out that the housing situation impacted on Covid-19-related health risks among which the negative effects of overcrowding and lack of in- and outdoor space during periods of self-isolation contributed to the unequal impact that the pandemic is having on different groups in the UK. Here, data-driven decisions can minimize the unequal impact of the pandemic while increasing more participation of the vulnerable groups. Managing crises necessitates evidence-based decision making that requires rapid feedback cycles of data-driven learning and data sharing.

However, in order to withstand the challenges associated with crises and uncertainties, new technologies can be incorporated more effectively so that broader social, economic and ecological impacts can lead to a wider social, technological and environmental context (Markolf et al., 2018). Galaz et al. (2021) argue that the use of AI and associated technologies in the pursuit of sustainability goals could give rise to systemic risks such as the collapse of an entire financial system or market. These risks could hinder progress due to problems associated with personal identity and transparency, equal access to AI technologies and cybersecurity. On the other hand, it has been argued that in the case of emergencies, a stronger partnership can be facilitated between the public sector and the technology sector. There is a strong opportunity for the technology sector to partner with the public sector to improve threat detection and risk mitigation far beyond reacting to an evolving storm: “AI and data can also act as wingmen for the public sector, strengthening systems and infrastructure over time” (Kent & Herrington, 2021).

CONCLUSION AND FUTURE RESEARCH VENUES

Crises such as the Covid-19 global pandemic can often provide the impetus for rethinking what is desirable in and how to organize our everyday lives. Oftentimes, this reflection is tied to notions of embracing modern, advanced technologies to improve on societal outcomes. We saw this in the example of the Global Financial Crisis in the late 2000s. When the fourth industrial revolution became popularized in its aftermath as a solution to economic stagnation, the questions around preferences and management have arguably continued and intensified with ongoing discussions about AI and related technologies during the pandemic. As our chapter stresses, technological advancements alone are inadequate if broader social and ecological questions remain downplayed or ignored. For AI to truly deliver radical transformations, there is a need to engage stakeholders to address questions of how society, environment and economy can be (desirably) constituted. This requires a greater degree of participation and engagement so that the complexities associated with managing, preserving and enhancing our planet, people’s livelihoods and prosperity can be equitably and responsibly captured. Yet, the challenge of participation and engagement has been a long-standing one.

The use of AI raises new possibilities, questions and problems around how we can better organize more inclusive participation. For instance, while AI increases the potential for drawing on (big) data analytics that can improve designs of the built environment, we also see that AI can also serve to entrench and deepen existing inequalities. What are the trade-offs for increasing the speed and scale of such analytics? Who are we excluding as a result of this drive towards the adoption of AI, such as the digital poor who either do not leave or leave different kinds of digital traces in the internet? How will AI alter the dynamics of participation and reshape the ethical interactions between professional expertise, machine intelligence and locally situated knowledge in the social world?

As our brief overview indicates, AI has already been used in many different fields in searching for remedies towards building healthy environments in the post-pandemic recovery. Yet, where the built environment is concerned, AI is also supporting existing logics of the built asset lifecycle, from design to construction to post-occupancy service and maintenance. To what extent is AI reinforcing existing (inefficient) rationalities of producing the built environment, and to what extent can AI potentially disrupt the order, process and methods to deliver improvements that can create safer, healthier and more inclusive built environments? How will AI be used to stimulate changes in human behavior that can lead to use of the built environment in less wasteful and more sustainable ways, while safeguarding privacy and personal freedoms? Understanding the power relations between human and machine will thus be an increasingly significant line of inquiry in the future as we design and learn lessons from the use of AI in producing better built environments in the the post-pandemic world.

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