The role of complexity for digital twins of cities

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We argue that theories and methods drawn from complexity science are urgently needed to guide the development and use of digital twins for cities. The theoretical framework from complexity science takes into account both the short-term and the long-term dynamics of cities and their interactions. This is the foundation for a new approach that treats cities not as large machines or logistic systems but as mutually interwoven self-organizing phenomena, which evolve, to an extent, like living systems.

A digital twin is a model that is as close as possible to a physical system such that it can be used for many practical purposes. The twin shares information with the counterpart system in terms of its inputs and outputs. The system and its twin work in concert, where the twin can inform, control, assist and enhance the original system[1]. Digital twins are being used, in particular, to represent the physical (infra)structure of complex systems, such as cities (but also products and persons), in an increasingly detailed and realistic way[2–4]. Current digital twins typically employ data analytics, physical modeling approaches[5] associated with the Internet of Things (IoT)[6], machine learning and artificial intelligence, as well as a variety of modeling styles and types that have recently emerged[7].

Notably, digital twins of cities have recently attracted the attention of scientists, engineers, and policymakers. In this context, digital twins are largely concerned with real-time operations of cities, such as their physical flows. They are increasingly being used as new design and management tools for both short- and medium-term planning[8]. This approach is based on large amounts of data from human and physical systems, where automated sensors are increasingly available to deliver such data in near real time.

Although some digital twins have been proposed as models for the long-term evolution and planning of cities, they are often focused on the management of shorter-term dynamics, such as the 24-hour city, rather than changes over years or decades[2]. In addition, cities grow as the result of a multitude of mutual interactions or bottom-up decisions, which is very different from most digital twins that have been proposed for cities as top-down created constructs[9]; such constructs resemble more machines than organisms. Because everyone perceives and experiences a city differently, there are individually different behaviors, expectations and representations, which are hard—if not impossible—to capture in a single digital twin.

Overall, cities are the outcome of multiple interactions between their components[10–13]. This is a property that can be well explained by means of complexity science—meaning, the science of complex systems—which embraces different scales. Complex systems are often defined as systems that are 'more than the sum of their parts'. This cannot be fully explained from the properties of the system components[14], but requires the consideration of their nonlinear or network interactions. In fact, complex (dynamical) systems are systems in which the constituent

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elements interact with and adapt to each other in a nonlinear way, self-organizing often across multiple networks and scales, which typically results in the emergence of new system properties.

In the case of urban areas, citizens interact directly and indirectly with each other. Such a combination of patterns is typically quantified in the form of a network[15]. The interplay among citizens determines traffic jams, segregation phenomena and other spatial distortions, as well as supply-side problems such as unexpected shortages of services and sometimes their oversupply. In all of these cases, a suitable network representation often allows one to quantitatively compute relevant properties of such systems, thereby providing useful representations of their fragility or resilience.

In this Perspective, we argue that combining the digital twin approach with a complexity science approach can have huge benefits for cities. On the one hand, the reproduction of all relevant city features in a digital twin is a necessary condition for better calibrated, validated and hence more realistic models. On the other hand, the recognition of systemic effects arising from 'individual behaviors' is expected to deliver more explicable and trustworthy models and results. In particular, for the latter, it is helpful to use mathematical instruments such as graphs to describe the system elements and their interactions. Network science can be, thus, a key method for articulating how interactions between the elements of a system and the processes driving it can be modeled.

Why digital twins are not enough

There are many theories as to how cities are structured and how they evolve, and most of them relate, at some juncture, their socio-economic functioning primarily to their physical aspects[16]. This also applies to digital twins, which tend to ignore the extensive complexity of a world, where psycho-social, economic, physical and environmental features are deeply entangled and cannot be easily separated out. In fact, contemporary approaches to creating digital twins are often surprisingly 'materialistic' or 'physicalistic', typically based on measurement data about the functioning of buildings, streets and natural environments, whereas human, social and cultural activities that drive the socio-dynamics of cities are often barely featured[9].

We acknowledge that data-driven methods based on measurement sensors, IoT, big data analytics and machine learning have become quite powerful. However, they tend to bias digital twins towards reflecting our physical world, while it is widely accepted among urban policymakers, planners and even the wider public at large that there are many things in cities that cannot be easily captured in physical terms. Moreover, these methods have some further limitations owing to: measurement limits (involving sample bias and uncertainty); computational limits (such as NP-hard computational problems[17]); mathematical constraints (such as undecidability or incompleteness[18] or halting problems[17,19,20]); common issues of data analytics (such as overfitting[21], parameter sensitivity, ambiguities, uncertainties and relevance of context); and limits of machine learning approaches (such as the use of 'black box algorithms'[22]). As a result, more and more data does not necessarily result in a deeper understanding, but can instead result in the emergence of further problems with digital twins as well as in the social systems, which are being managed using such twins[23].

Immaterial relations

Today's digital twin approach is often based on data-driven and machine-learning-based massive agent-based simulations, which may produce highly detailed lookalikes. But many digital twins do not consider immaterial, invisible and barely measurable interactions well. To illustrate the importance of this, let us discuss some well-known phenomena in societies[24]. For instance, conscious populations give words and patterns a meaning. These meanings matter for human intentions, decisions, behaviors and interactions, but they may change among groups and over time. Moreover, people spontaneously form groups. These have diverse identities, which influence the intentions, behaviors, characteristics and interactions of their members. Social processes further produce social capital such as reputation or trust[25]. They also create culture and values, which influence individual consciousness and collective behavior[26]. A mere representation of the structure and population of a city fails to reproduce those social phenomena, at least without proper consideration of evolutionary features connecting the individual with the mesoscale and macroscale.

In short, the traditional digital twin approach tends to overemphasize the physical components of a city, thereby massively oversimplifying human interactions. This can cause data-driven governance and planning to fall short. When used to control a system, it may eliminate serendipity and chance, diversity and pluralism. This may affect creativity, innovation and (co-)evolution, meaning properties that are important for a system to flexibly adapt, improve and thrive. As a consequence, one might get 'trapped in the matrix'. That is, using digital twins for control could 'freeze' certain organizational patterns, thereby preventing the successful adaptation to a changing environment and context[27].

Systemic failure or collapse

As a result of social interactions, systemic failures might result. A classical example is given by the financial system[28,29]. Here, the system is defined by financial institutions. One way to measure the mutual network dependencies is the credit network among banks. Institutions that regulate the liquidity market, such as central banks, are regularly running stress tests to quantify the robustness of the system versus the risk of bankruptcies, assuming some external shock (such as the recent war in Ukraine, which triggered large fluctuations in the price of oil and gas). However, such stress tests can lead to wrong results if one just considers that banks are either functional or bankrupt. For example, a bank may still operate while being on the edge of bankruptcy. Only its network of debts allows one to evaluate the degree of the distress of the financial institution[30]. Such underestimation of the risk can trigger further disruption. Furthermore, if central banks were to control the transactions of consumers, the effects would be even bigger. Hence, traditional reductionist approaches that attempt to understand cities from the properties of their parts often fail, mainly due to their lack of considering multi-level interactions and complexity[31].

Scalability features

A further important problem of digital twins that needs to be addressed concerns their scalability, which in some sense pertains to real cities as well. In general, as a city gets bigger, its representation typically does not scale linearly with densities, areas and size[32,33]. Bigger cities are qualitatively different from smaller cities and, in general, the bigger a city the greater the agglomeration or clustering effects that increase their inventiveness, innovation and wealth. When defining a city in terms of its physical or functional boundaries, these often extend far beyond the administrative boundaries, thereby better representing the interacting natural and human elements of a city's system[34]. This is important as it can make an enormous difference to the scaling and actual properties of a city[35–37].

Cities should be represented at the scale of their whole extended urban region[8]. When considering the city in this wider context, the current concept of local digital twins might be too limited. In fact, many implications of the complexity of cities need to be analysed in a global context—for example, those that are relevant for scenario forecasting associated with pandemics[38,39]. In short, the boundaries of a city are uncertain and, therefore, seeing a city in anything less than its global context is a problematic simplification.

How complexity science can help

New technology will continue to help unleash the power of digital twins through various kinds of sensing associated with, for example,

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IoT, which is already producing a previously unimaginable amount of data quickly and cheaply. The interpretation of these data, however, and the quality of analysis is still problematic. In many cases, it is also necessary to reduce the size of data and filter them, to handle issues such as sustainability and societal resilience[40,41].

Complexity science has the potential to address these issues by combining data-based and hypothesis-based approaches. For example, network models are being used to represent different interests of people, their skills, behaviors and habits. Complexity through network modeling also allows for a shift in perspective. In fact, most models of cities still treat cities as systems built from the top down. Complexity science changes this perspective and allows one to consider cities as multi-level systems[42,43], which involve many bottom-up processes. This makes it possible to explain highly important signatures such as power laws and scaling[44], as well as long-range correlations across the various networks[45]. The fact that such systems evolve from the bottom up introduces a degree of uncertainty and unpredictability that needs to be factored into the use of digital twins when generating, testing, evaluating and implementing simulation scenarios for future cities.

Urban policymakers[46], analysts, regulators and planners need to be made continually aware of the many interconnected facets of the planning problem. Therefore, to ensure future sustainability, fairness and adaptability[47], different modeling frameworks need to be considered. In short, urban policy calls for models that capture the co-evolutionary nature of cities, so that future emergent developments can be best anticipated and adapted to. Rather than just being formal representations of the problem at hand, models help one to focus the analysis on relevant questions, thereby informing one about the kind or part of data to use.

We shall see in the following that to deal with the points raised in the above section, we need to consider the multiple intertwined interactions between networks, which develop at different levels and dimensions, and mutually influence their functioning trajectories of development or failure. The great strength of complex systems is their ability to self-organize efficiently, resiliently and favorably, if suitable interactions are in place. This may be supported by federated learning approaches.

Quantifying immaterial relations

Some of the quantities that may not be measurable directly (and, therefore, are often neglected by digital twins) result from interactions in social communities, which may be considered by network analysis. Social groups are an important example to illustrate the coarse graining of data. Their relationships can be described at different scales (where a module at the lower scale becomes a node at a higher scale)[48]. Multilayer networks are the mathematical representations of such structures, as shown in the left part of Fig. 1, which illustrates a city system.

Such structures appear as the natural topological blueprint[49,42] of complex transport[50,51], information[52] and energy flows[53]. Social networks in cities are multi-layered also, because they comprise professional, friendship, institutional, religious and other channels that overlap and sometimes have very strong mutual effects. In addition, these networks interact with the infrastructural networks[48], as depicted in Fig. 1. Parts of the local networks also depend on bigger networks that extend beyond the boundaries of the city[54]: at the regional scale, commuters coming from outside of the city often have impacts that reach beyond the units of political governance associated with their commute. At the global scale, each city is embedded in multiple national and global exchange networks for products and services, firms, migrants, cultures and ideas. These create channels of collaboration for innovation, imitation and concurrence, which are relevant for planning future cities.

Public urban mobility systems are composed of several transportation modes connected together. Many studies in urban mobility still ignore the multi-layer nature of transportation systems, considering only aggregated versions of these networks. This often treats layers as if they were isolated from each other, leading potentially to misplaced conclusions[55].

Complexity and resilience

As open, 'non-equilibrium' systems, urban areas can be considered to resemble living organisms; such a feature can be considered by (co-)evolutionary approaches and by defining a 'city's metabolism'[53]. Such a perspective is also suited to study the resilience of cities with respect to external shocks. As the above-mentioned layers are interdependent, the information about any specific layer and the dynamics of the cascading effects between them is often lost when aggregating network data. This is particularly relevant for the issue of resilience, which is strongly affected by couplings between layers[56]. Current research into multiplex networks considers new ways in which different locations in the city are connected, based on a wide variety of material and information flows.

Evolving layers may include the physical (natural and artefactual) environment, as well as social structures, networks, movements and the immaterial properties of their interactions. For example, some new infrastructures such as rail or road systems could be beneficial for the whole city's accessibility, but at the same time they could also create new local issues of segregation, pollution or risk of accidents. This is why the variety of scales and dimensions of the city is crucial for articulating the way a city functions. The systems developing at different interdependent scales are far from equilibrium, potentially changing environmental and societal systems even globally[57]. The technical features of multi-layer networks (communities, bottlenecks, centrality, fragility) allow one to describe these evolving multi-level socio-ecological patterns. In general, the framework of complex networks allows one to follow the evolution of interactions between social and natural dimensions at different scales. Such features are in strong agreement with Elinor Ostrom's work on 'managing the commons'[58,59]. Cities are a true example of socio-ecological systems in the sense of Elinor Ostrom: these are capable of an effective and sustainable management of the commons, based on institutions that may arise in a self-organized manner from the interactions between individuals. Such institutions can successfully (self-)govern the commons.

To deal with these problems, measures of centrality (which define the part of the network nearest to all the other parts) can represent intangible quantities such as the importance of areas to protect the system from collapsing. Networks also offer new ways to understand coordination and cooperation[60].

Multi-scale approach

Networks allow one to focus on quantitative measurements such as the flow of energy in a specific area; see, for instance, Maranghi et al.[61], where the authors consider that the sustainability of a city is reflected by a complex, dissipative system[62], which must be assessed considering energy, material and information flows. These exist at scales that offer an overall view, while giving detailed insights into processes that determine how the city functions, meaning how flows are transformed and efficiently used at a smaller scale. This is essential information as it may guide the world towards fairer, healthier and more liveable cities.

Complex systems can play an essential role in figuring out and illustrating how these diverse and widespread goals are interconnected at different scales and how they may be realized[63]. In such a way, it will also be possible to take bottom-up phenomena into account. This is particularly important in our rapidly changing world, which is determined by interactions, positive feedbacks, random noise, and network cascades. Decentralized control can perform better in complex systems with heterogeneous elements, large degrees of fluctuation and short-term predictability, because of greater flexibility to local conditions and greater robustness to perturbations.

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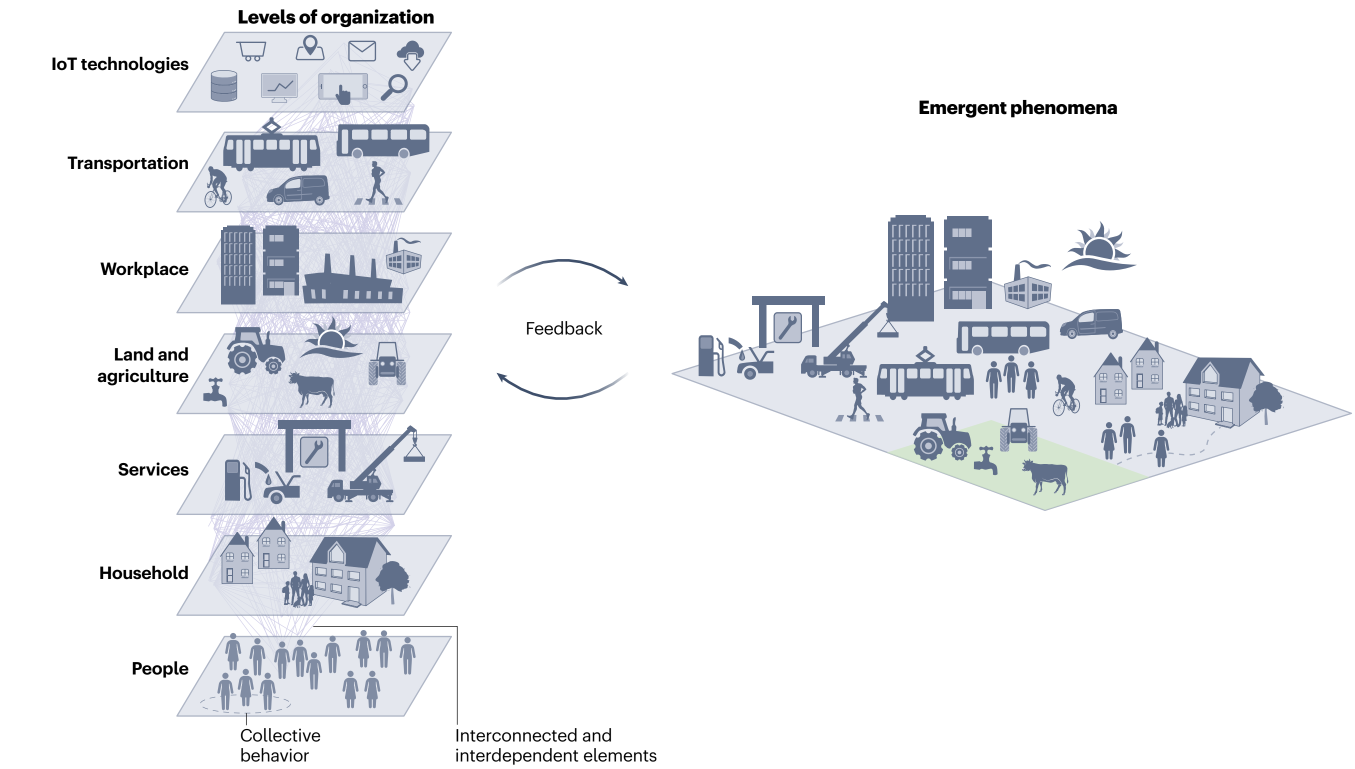

Properties and features of complex systems
- Interconnected and interdependent elements
- Networked hierarchical connectivities
- Adaptability
- Self-organization
- Emergent phenomena
- Nonlinear interactions
- Collective behavior
- Non-equilibrium dynamics
- Limited predictability
- Different levels of organization
- Threshold effects

Fig. 1 | Features of complexity. Schematic illustration of a city as a complex system generating emergent phenomena, something that is not captured by a digital twin alone. A city may be represented in terms of its different interacting layers (left), which give rise to emergent properties such as clusters of communities and traffic patterns (right). The properties and features of these types of system are described in the box (bottom).

Challenges of integrating complexity science into digital twins

As discussed throughout this paper, the data-driven approach represents a major leap forwards compared with previous frameworks. It is, however, insufficient to create an accurate model of our complex world, which is characterized by limits to what is measurable, predictable and controllable[64,65]. However, integrating complexity with digital twins, while absolutely necessary, is not without challenges.

One of the challenges that need to be tackled is deciding the right amount of data and selecting the best data to address each issue. Attempts to produce an exact digital copy of the world are obstructed by many factors—not only necessarily by a lack of data but also by some laws of mathematics and of nature (see 'Why digital twins are not enough'). Surprisingly, less parameters or models with noise can sometimes generate better results—and simpler models often have more predictive power. Another difficulty arises from the fact that working with one big dataset that attempts to cover every known feature of the city and, then, filtering out the data needed for a particular application, may not always be effective. The bigger the data, the less efficient is the filtering, and sometimes one does not see the forest for the trees. Also, the well-known problem of overfitting often plagues approaches that seek to extract patterns from big data using various kinds of machine learning techniques[66,67]. The focus is typically put on a detailed representation of the system's components, while their interactions are often a lot more important for understanding the behavior of complex systems[68]. It is then clear that much care is needed to properly deal with data to benefit from the 'complexity toolbox'.

Related to the previous issue is the challenge of obtaining exact data on the interactions of the system's components. This inherently limits reproducibility, no matter how much data about the system's elements are available. Unfortunately, interactions may be probabilistic or their effects may occur with delays, such that the exact kinds of interactions are often hard to determine from available data. They may also vary across different scales, ranging at least from human–human interactions to interactions between humans and the environment. It might be necessary to study cities as ecosystems. Plant species, for example, find ways to discover mutual convenience through the slow and continuous adjustment of their relationships, which is guided, generation after generation, by evolution. It is owing to the process of co-evolution (by which human environments, buildings, networks, plants, animals, ecosystems and cultures advance in interactive ways) that cities can develop and thrive, particularly when interactions are synergistic and symbiotic. Consequently, planning interventions need to consider bottom-up interactions, which is central for a proper, generative understanding of urban dynamics[69], and to enable thriving cities. Similarly to living systems, cities evolve to generate morphology, networks, information, fabric and functionality, which define the essence of their complex nature[70,71].

Beyond dealing with data and having a precise picture of the interactions of the city components, a further challenge arises as the complexity picture must reflect the behaviors and interactions of

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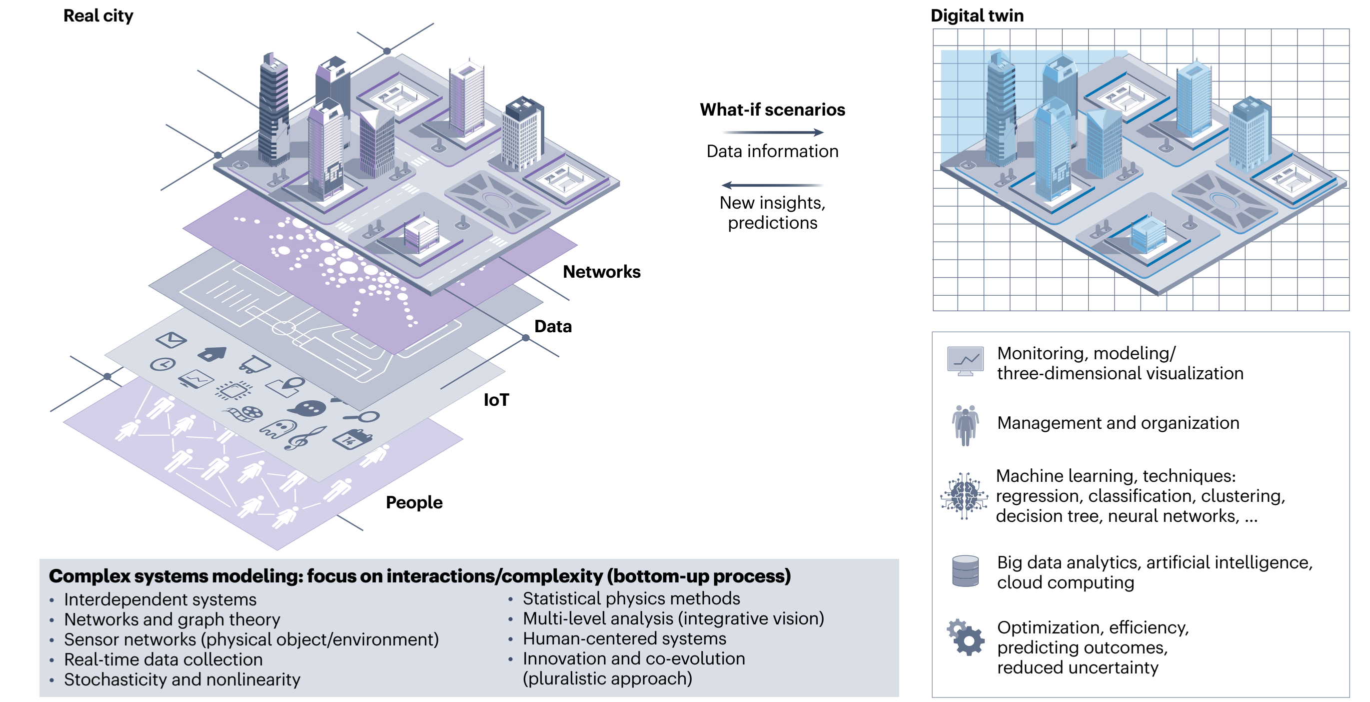

Fig. 2 | Complexity and digital twins. Left: the complex systems approach extracts selected information from a system's components and their relationships to simulate essential aspects of the system based on suitable simplifications, allowing one to understand collective dynamics resulting from bottom-up interactions. Bottom left: using big data and machine learning, the digital twin approach constructs a detailed copy of the city (right), which is used to manage the real city and develop it further.

their actors, as cities are designed, built and planned by the people, for the people. This in turn involves mapping many layers of complexity defining the city system[72–74]. This occurs, as we have noted, because the interaction networks between people in cities are multi-layered, corresponding to different arenas in which city life takes place. But this is not the only challenging issue of complexity, as human interactions lead to second- and higher-order phenomena[75], when people themselves detect the presence of emergent features and act accordingly. In addition, it is important to incorporate the many timescales that can be involved in these processes. This is crucial for the complex systems perspective to improve the implementation of digital twins.

Examples of second-order emergent phenomena abound, beginning with social norms[76]. Such second-order emergence arises[77], for instance, when a norm promotes cooperation or collective action[78,79]. The dynamics of the underlying feedback loops depend on both external and idiosyncratic factors, leading to a very complex dynamics, taking place over very different timescales[79]. A paradigmatic example is that of pedestrian route choice, a process involving information perception, information integration and obstacle avoidance, where individual decision-making responds to information in context-dependent settings[80]. It thus becomes apparent that an accurate and useful description of these multi-time and multi-scale feedback processes taking place on multi-layer networks is a key challenge in defining proper digital twins for cities, where complex structures, functionalities and dynamics are vital.

Another important issue is related to the ethical norms and quality standards required by digital twins. To properly design cities for humans in harmony with nature, the concept of a digital twin needs to be extended to the social and ecological domain in a value-sensitive way, respecting privacy and human rights[67]. The fact that a city is composed of physical, biological and social entities should be addressed by digital twins that take the various known challenges into account[24] (Fig. 2). Even more importantly, one needs to consider that many of the qualities that matter for human and city life, such as freedom, creativity, well-being, friendship, trust and dignity, are hardly quantifiable but should not be just neglected or treated like noise. Setting up a thorough framework including all possible ethical factors involved in digital twins constitutes a very important complexity challenge, given the difficulties to predict collective outcomes from individual circumstances.

Last but not least, there is currently a lack of complexity scientists in many areas of science and engineering, and hence a lack of knowledge regarding what is special about complex systems and their behavior, and what this means for the design and use of digital twins. Accordingly, education in complexity science should become an integral part of education in all areas, where digital twins for complex systems are being developed and used. In addition, many digital twins are based on proprietary software solutions, and hence it is not knowable to many scientists how they work exactly; neither can these scientists easily improve such digital twins and develop them further. Therefore, one should explore open-source arrangements.

Embracing complexity for smarter cities

So far, big data has not removed the need for theory, and it has not made the scientific method obsolete, thus questioning Chris Anderson's polemic more than a decade ago[81]. Indeed, exactly the opposite has occurred. When it comes to dealing with bottom-up emergent behavior, which one likes to understand, explain, predict and design for, multi-scale complexity-based approaches are urgently needed. A key problem of current digital twins is that they fall short in representing the complete set of relevant interactions between physical assets, processes and systems. For the reasons explained in this Perspective, complexity science can be a potential solution to this problem. A list of features characterizing digital twins and complexity science is presented in Table 1. As it turns out, they are largely complementary, which suggests the need to combine both approaches.

Table 1 | Strengths and challenges of digital twins and complexity science

Digital twins	
Strengths	**Challenges**
Data-driven	Intangibles (for example, norms and values; human, social and cultural issues)
Real-time analytics	Errors in measurements
Parameter fitting	Overfitting and lack of validation
Optimization	Self-organized phenomena
Design and planning	Participation and co-creation
Machine learning of system characteristics	Explainability ('black box algorithms')
Complexity science	
Strengths	**Challenges**
Focus on interactions	Data availability
Consideration of (multi-level) networks	Data availability
Self-organized dynamics	Computational power for large-scale computer simulations
Understanding of 'tipping points'	Determination of their exact values
Cascading effects	Fixing systemic instabilities
Ethical issues can be considered	Value-based engineering

Despite pervasive measurements at all scales, from satellites down to nanoscale sensors, building a fully fledged and realistic model of a complex system incorporating problem-solving capacity remains a grand challenge. Actors and stakeholders interact through economic channels, through emergent phenomena such as social norms and through their individual emotions and personal history. This gives rise to a highly nonlinear co-evolution in response to environmental changes and governance inputs or related forms of decision-making[82]. It also implies ethical challenges[67]. At the same time, however, it opens up a way for digital twins to take bottom-up emergent processes into account. Human thinking, behavior and the material world impact each other in complex ways that may be conceptualized through multi-layer systems of interaction networks.

Evolutionary algorithms can serve as inspiration to develop adaptive approaches to search for novel solutions. Nature adapts at multiple timescales, and one can learn to apply its success principles to urban contexts[61,62]. Using the fastest (quantum) supercomputers, artificial evolution can, to some extent, be simulated, thereby allowing one to accelerate evolutionary timescales beyond the speed of cultural evolution. This may reveal how to use local feedbacks in a way that empowers self-organizing, co-evolving systems.

As we argued here, the way to achieve better planning of urban areas is not by working solely with digital twins, but by combining them with complexity science. This can help to more successfully bridge science and engineering with policymaking, governance and participatory approaches, as well as when exploring various 'what-if scenarios'. Among the various objectives of such an approach, we list here some particularly important ones.

- Enhance knowledge (co-)creation, exchange and management at all levels of government, civil society, the private sector and other relevant stakeholders.
- Help increase the capacity (human, financial and institutional) of policymakers and civil society at all levels to develop and progressively implement urban policies, offering participatory platforms for capacity building.
- Provide networking platforms where all levels of government, civil society, the private sector and other relevant stakeholders can engage in the development process. To this end, the proposal for the 'city of opportunity' concept, with a city planning based on a network of 'neighbor microcosms'[83] is a possible way forward.

We need digital twins that are able to embrace the potential of complex systems, to empower citizens and stakeholders, facilitating a participatory dialogue. However, we need to go beyond digital twins to provide a public 'cyber'-space for community interaction, where citizens can voice their opinions about considered interventions, propose changes, point to problems and suggest solutions. In this context, the combination with complex systems could promote participatory, collaborative exploration. This would be based on interactive 'what-if scenarios', engaging citizens and local representatives, thus enabling policymakers to make well-informed and better-fitting decisions[84]. Simulations are an essential tool for studying complex systems[85].

Advances in traditional digital twins could certainly benefit the scientific study of complex systems, because they will offer data to calibrate and validate models, but also accelerate problem identification and solution. This lies at the heart of our argument for the urgent consideration of complexity science while building and using urban digital twins.

In conclusion, as the processes of networking and urbanization in our globalized world evolve[86], one will progressively face the key features, problems and opportunities of an increasingly complex world. When designed or operated without proper scientific validation and explanation, or without good insight and human oversight, digital twins may generate serious issues for the affected citizenry, also in regards to privacy and transparency[24]. However, if properly used and combined with complexity science and citizen participation, instruments like digital twins would allow one to come up with adaptive, efficient, resilient and sustainable solutions that are compatible with democracy, human rights and innovation. The idea is not to push the reproduction of the system to the limit of a one-to-one scale, thereby profiling everyone, but rather to extract trends and laws from the digital representation as shown in Fig. 2. Hence, when designed and operated well, digital models of the world (or certain aspects of it) can offer formidable policy instruments. This applies not only to the management of cities but also to the co-evolution of many evidence and data-based information ecosystems, which can foster a new collaborative relationship between citizens and policymakers.

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