Complexity Science for Digital Twins

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Abstract

City planners and urban policy makers require simulation models to understand, forecast, design, and manage urban areas so that cities can become more sustainable, equitable, and livable. Recently, the idea that one might build 'digital twins' of cities has attracted the attention of scientists, engineers, and policy makers alike. However, to unleash the full potential of data, science, and technology, theories and methods drawn from the complexity sciences are urgently needed to guide the development and use of such twins. Complexity science approaches take various perspectives on the short and long term dynamics of cities as well as their spatial interactions. This is the foundation for a new paradigm that treats cities as mutually interwoven self-organized phenomena, which evolve, to an extent, like living systems rather than machines.

Keywords: Complex Systems, Digital Twins, Urban Simulation, Planning Models

1 Introduction

A digital twin is a model that is as close as possible to a real system without it actually being that system. It shares information with the system in terms of its respective inputs and outputs. In this way, 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 in an increasingly detailed and realistic way [2–5]. Current digital twins typically employ data analytics, technologies associated with the Internet of Things (IoT)[6], machine learning and artificial intelligence (AI), plus a variety of modelling styles and types that have recently emerged [7].

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Digital twins are largely concerned with the real-time operation of cities, mainly with respect to their physical flows. They are increasingly being used as new design and management tools for both short and medium term planning [8]. Large amounts of data from human and physical systems, where automated sensors are increasingly available to deliver such data in near real time, are the basis of this approach. Although a handful of digital twins have been proposed as models for the long term evolution and planning of cities, they are mainly focused on the management of shorter term dynamics such as the 24-hour city rather than changes over years or decades.

In modelling many systems across the sciences, complexity theory has emerged during the last half century where the focus is on the way systems evolve as the product of a multitude of bottom-up decisions. This is consistent with the way cities grow but it is very different from most digital twins that have been proposed for cities as top-down constructions more like machines than organisms. Everyone perceives and experiences a city differently. This implies individually different behaviours, expectations and representations which are hard if not impossible to capture in a single digital twin. Moreover, for a city to work well, it must embrace this great variety of behaviours which reflect important differences revealed in complex patterns of segregation and polarisation. Cities provide crucibles of opportunity and thus provide infrastructures well beyond the physical domain, encapsulating social as well as economic activities that provide the momentum for city growth and increasing wealth but also poverty traps for the less able.

Therefore, the most appropriate modeling of cities goes well beyond the realization of digital twins which simply reflect the physical reality of a city. Data pertaining to every aspect of the city needs to be defined and this is not simply accumulations of people, activities, buildings, and flows. Before this mass of data is defined, it is essential to define the theoretical perspectives central to how the city which is to be twinned with the digital model is conceived. Therefore, it is essential to reproduce this mass of data in computer models identifying the most appropriate abstractions for what one is observing [9]. A clear focus on scale in space and time is essential and as Jorge Luis Borges underlines [10], one must avoid making 'a map' as large and as detailed as the entire domain one wishes to describe. Abstraction is thus an essential construct in the definition of a digital twin but it is often sorely absent.

Cities are the outcome of multiple interactions between their components [11–14], a property that needs to be explained by means of the complexity sciences that embrace different scales. "Complex systems" are systems where the constituent elements interact and adapt to each other, self-organising in a non-linear way often across networks. Once the number of elements increases, new properties "emerge". For example, the property of water to be transparent or wet, or the property of fire to be hot are not determined from properties of single molecules. Similarly, the cultural identity of people is not simply explicable from the character of individuals, but it is essential to define city life.

Typically, complex systems are characterised by dynamic rather than static behaviors and probabilistic rather than deterministic ones. The common definition that "complex systems are more than the sum of their parts" can be explained by non-linear interactions, i.e. it cannot be fully understood from the properties of the system components [15]. Surprising and sometimes even paradoxical system behaviors (such as "slower-is-faster effects" [16]) may occur. Furthermore, complex systems are rarely predictable and often uncontrollable, particularly when "systemic instabilities" occur. Depending on the model and its respective parameters, attempts to change the system may be ineffective, or small changes may have a large impact as in the case of "chain reactions", "domino effects", or "phase transitions". Due to non-linear interactions, there may be unwanted side effects, positive feedbacks , or "cascades". Therefore, complex systems are difficult to understand. They are popularly classed as 'wicked problems' by decision-makers and pervade data-driven and AI-based approaches. For example, the "Game of Life" whose dynamics are produced by a simple cellular automaton based on very few rules [17], are impossible to simulate using neural networks.

For these reasons, complex systems are often studied through computer simulations, using agent-based modeling and other micro-simulation approaches. It turns out that complex dynamical systems tend to have emergent system properties and behaviors, which occur from self-organization based on interactions among the system components. The resulting properties and behaviors change at certain "tipping points", but are otherwise robust to reasonably large perturbations. This makes them both adaptive and resilient which are critical properties of interest in cities.

If the interactions among the system elements are well specified, a complex system will efficiently and automatically produce desirable properties and behaviors based on self-organization. As we shall see, the most suitable mathematical representations of complexity are often provided by network theory [18]. In the case of urban areas, citizens interact directly and indirectly, and this can determine traffic jams, supply-side problems such as unexpected shortages of services, segregation phenomena, and other spatial distortions. But a network representation allows one to quantitatively compute relevant properties, thereby, providing a useful representation of the resilience or fragility of a system.

Note that in real-world applications of complexity science, the natural interactions of the system components may be modified by real-time measurements and feedbacks, using the Internet of Things and related technologies. Such digital assistance can promote desirable self-organization. Suitable interactions may be identified by the field of "mechanism design". In many cases, local feedbacks and a minimally invasive approach are recommended. For example, it is possible in this way to dissolve traffic jams on many kinds of network system [19] [20], even without the centralized coordination of a traffic control centre.

In this paper, we propose that, combining the digital twin approach with a complexity science approach can have huge benefits for both areas and approaches. On the one hand, combining agent-based and other simulation-based approaches with data science and machine learning approaches is expected to lead to better calibrated and validated, hence, more realistic models. On the other hand, combining digital twins created by data-driven and machine learning approaches with complexity science models is expected to deliver more explicable and trustworthy models and results, which allow for a better understanding of the respective system and how it can be managed successfully. It is helpful, in particular, to use mathematical instruments such as graphs to define systems elements and their interactions, and network science is thus a major method for articulating how interactions between the elements of a system and the processes that drive it, can be modelled. Much of this is missing from the current generation of digital twins.

Complexity science allows us to reveal emergent behaviours, historical path dependencies, innovation, and unexpected effects that differ across different models [18, 21–23] — even though most of this complexity is captured in various types of social clustering and segregation [24, 25], spatial organization [13, 14, 26, 27], hierarchies of transport, [28, 29], congestion and traffic jams [30], multilevel management of urban policies [31], processes of opinion formation [32], and the evolution of culture and language [33–35]. Moreover, interactions between different domains of urban life such as work, health and well-being, education, mobility, family life and so on are increasingly relevant. Think, for example, of the changes in the retail, health and education systems as well as in the organization of work and leisure time during the recent pandemic [36–38]. At different time scales, these various dimensions create constraints and opportunities for cities in combination with multi-dimensional [39–41] and multi-level interdependencies between local, national, and global trends. Such multi-level and multi-dimensional complexity, we argue, should be reflected in digital twins [42].

2 Why digital twins are not enough

There are many theories as to how cities are structured and how they evolve but most established approaches relate their socio-economic functioning to their physical form. However many proposals for digital twins are strongly orientated to their physical configuration and tend to ignore the extensive complexity of a world where social, economic and physical features are deeply entangled and cannot be easily separated out. Despite their underlying digital representation, contemporary approaches to creating digital twins are often surprisingly “materialistic”, or ”physicalistic” based on data that is streamed from the functioning of buildings, streets and natural environments in which urban populations and activities barely feature. Data-driven methods which generate twins are produced from arrays of fixed and mobile sensors which tend to bias such models to the physical world

These arrays of data also tend to bias such twins to features that can be easily measured whereas it is widely accepted by urban policy makers, planners and even the wider public at large that there are many things in cities that are not measurable. Thus digital twins tend to reflect the Internet of Things, big data analytics, and machine learning. While this approach is becoming more powerful, it also has some noteworthy limitations such as:

- measurement limits involving sample bias and uncertainty;
- analytical limits (such as NP-hard computational problems [43], undecidability or incompleteness theory [44]; and halting problems [45, 46]);
- data analytics issues (such as "overfitting" data[47]; parameter sensitivity; ambiguities, uncertainties, and the relevance of context);
- limited accuracy, "slowness", and "rigidity" of machine learning associated with "black box algorithms" [48].

Therefore more and more data does not necessarily result in a deeper understanding, but can instead result in the emergence of further problems in digital twins as well as in the social systems which are being managed using such twins [49].

In developing digital twins, there are rarely any attempts at endowing such twins with opportunities for exploring the future in a predictive or design context. In contrast, in the complexity sciences, one can make and test hypotheses, thus varying key model assumptions, often in the sense of "what ... if" scenarios. Hence, in contrast to data-driven digital twins, complexity science aims at exploring various options. It attempts to define, if not model, immaterial, perhaps even invisible and barely measurable interactions between material objects or living things. The results of this modelling are then validated using empirical, experimental, or measurement data. This is little different from the long-standing practice of developing the best predictive models in contrast to most digital twins that are often silent when it comes to future forecasts of their system of interest.

To illustrate this point, let us look at some non-material properties that are considered to be important for human systems and societies [50]. For instance, conscious populations give words and patterns a meaning. These meanings matter for human intentions, decisions, behaviours, and interactions, but they may change among groups and over time. Moreover, people spontaneously form groups. These have diverse identities which influence the intentions, behaviours, characteristics, and interactions of their members. Social processes produce social capital such as reputation or trust [51]. They also create culture and values, which influence individual consciousness and collective behaviour [52]. All of this is considered by complexity science to be emergent and non-material in nature as reflected in network interactions [18]. This is extremely important for the resulting system properties and dynamics, and with respect to cities, this has a highly significant impact on the quality of life.

In short, *the traditional digital twin approach tends to overemphasize the physical components of a city, thereby massively oversimplifying its human interactions* . This can cause data-driven governance and planning to fall short. When used to control a system, it may eliminate serendipity, chance, and resulting emergent properties such as creativity, innovation, and (co-)evolution, which are important for systems to flexibly adapt, improve, and thrive. In the worst case, one might get “trapped in the matrix”. That is, using digital twins for control could ’freeze’ certain organizational patterns and, thereby, suppress successful adaptations to changing environments and contexts. Systemic failures could be result.

This happened, for example, in the financial system, when interaction networks were not sufficiently considered during the 2008 recession [53]. [ADD Haldane, A., May, R. Systemic risk in banking ecosystems. Nature 469, 351–355 (2011). https://doi.org/10.1038/nature09659] We are referring to the credit network amongst banks where the institutions regulating the liquidity market such as Central Banks are regularly running stress tests to measure the solidity of the system. Assuming the case of some external shock (such as with the recent war in Ukraine where the price of oil increases dramatically, the risk of bankruptcy is continually being estimated. Such stress tests, however, can give wrong results, if one does not consider network interdependencies to measure the distress of the financial institution. [54].

Similarly, traditional reductionist approaches that attempt to understand cities from the properties of their parts often fail, mainly due to the lack of their consideration of their multi-level interactions and complexity. For example a simple multi-level network analysis made for the Spanish city of Zaragoza [55] was able to measure the impact of the creation of new bus or tube lines on each other. Multilayer networks are structures in which nodes (often but not necessarily the same ones) can be connected by different kind of interactions (edges) in any of several layers. Therefore different parts of cities can be connected by a bus line (one layer) or a tube line (another layer) or by economic connections between, for example, work and residential areas, as shown in the left part of Figure 1 below.

A further important problem that needs to be addressed for digital twins is their scalability which in some respects is the same question pertaining to the real city itself. In general, as a city gets bigger, its representation typically does not scale linearly with densities, areas, and size [56, 57]. 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. Defining a city in terms of its administrative boundaries or its physical or functional ones that often extend far away beyond its administrative boundaries, thus better representing the whole interacting natural and human elements of a city’s system, is all important [58] as this makes an enormous difference to this scaling and the actual properties of a city. [59–61]

It is important to realize that cities are open, non-equilibrium systems. In a globalized world, defining a city in terms of its physical boundaries is a difficult, perhaps almost impossible task. As a matter of fact, one of the most important features in the management of “the urban organism” is its responsiveness to citizen needs and this varies with respect to how a city is defined [62]. Cities should be reproduced at the scale of their whole extended urban regions [63] and it is only when we consider the city in this wider context that we see that the concept of the digital twin begins to fail. In fact many new interpretations of the complexity of cities that have important implications for scenario forecasting associated with pandemics [64] [65] need to be considered in a global context and this raises the question of what is a suitable digital twin once our focus is widened to the whole globe.

3 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, the Internet of Things 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. Also, while the advent of quantum computing could boost machine learning and optimization on previously unimaginable scales, some of the previously mentioned limitations still apply. For these reasons, it is essential to take a diverse approach, varying the scales of approach and considering the interactions between different dimensions as this is crucial for extending digital twins to deal with issues such as sustainability and societal resilience [66]. Complexity theory makes this possible.

This can be done using networks to model the different interests of people, their skills, behaviours and habits. Complexity through network modelling 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 [39, 41] that involve many bottom-up processes. These may explain highly significant signatures such as power laws and scaling [23] as well as long-range correlations across the various networks [67]. 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 [68], analysts, regulators, and planners need to be made continually aware of the many interconnected facets of the planning problem. Therefore, to ensure future sustainability, equity, and adaptability [69], different modelling 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. Models rather than simple formal representations of the problem at hand are particularly powerful since they allow us to concentrate the analysis on specific questions, and thereby filtering the data produced.

Typical non-measurable quantities emerge from community analysis in networks as fashions and habits change. Furthermore those groups (denser clusters or their subgraphs) also allow us to study relationships among scales when a module at the lower scale becomes a node at a higher scale. Multi-layer networks are the mathematical representations of the structure shown in the left part of Figure 1 which is a schematic city system. These are the representations of the interactions between individuals at various levels, or analogously the representations of the interactions of coarse grained groups of people or of their attributes in households, workspaces and so on. Links within one layer and across layers define many of the the "unmaterial" relations that Digital Twins fail to represent.

Such structures appear as the natural topological blueprint [39, 40] of complex transport [28, 70], information [71], and energy flows [72]. Social networks defining cities are also multi-layered because they comprise professional, friendship, institutional, religious, and other channels that overlap and sometimes have very strong mutual effects. In addition, these also interact with the infrastructural ones [73], see Figure 1. Parts of these local networks also depend on bigger networks that extend beyond the boundaries of the city [74]: at the regional scale, commuters coming from outside 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 in planning future cities.

Public urban mobility systems are composed of several transportation modes connected together. Many studies in urban mobility ignore the multilayer nature of transportation systems, considering only aggregated versions of these networks. This often treats layers as if they were isolated from each other, leading to the misplaced conclusions [75]. In addition, as layers are interdependent, the information about any specific layer and the dynamics of the cascading effects between them is often lost when considering aggregated network forms. This is particularly true with respect to resilience that is strongly modified by couplings between layers [76]. Current research into multiplex networks suggests new ways in which different locations in the city are connected, using a wide variety of material and electronic flows.

A multi-layer approach is also essential to define the environmental impact of a 'city's metabolism' [72]. As open, "non-equilibrium" systems, urban areas can be considered as living organisms; such a feature is easily considered by allowing layers to evolve. Evolving layers should include the physical (natural and artifactual) environment, as well as social structures, networks, movements, and the immaterial properties of their interactions.

For example, some new infrastructures like rail or road systems could be beneficial for the whole city's accessibility but 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 to articulating the way a city functions. The systems developing at different interdependent scales are far-from-equilibrium, changing environmental and societal systems globally [77]. The technical features of multilayer networks (communities, bottlenecks, centrality, fragility)

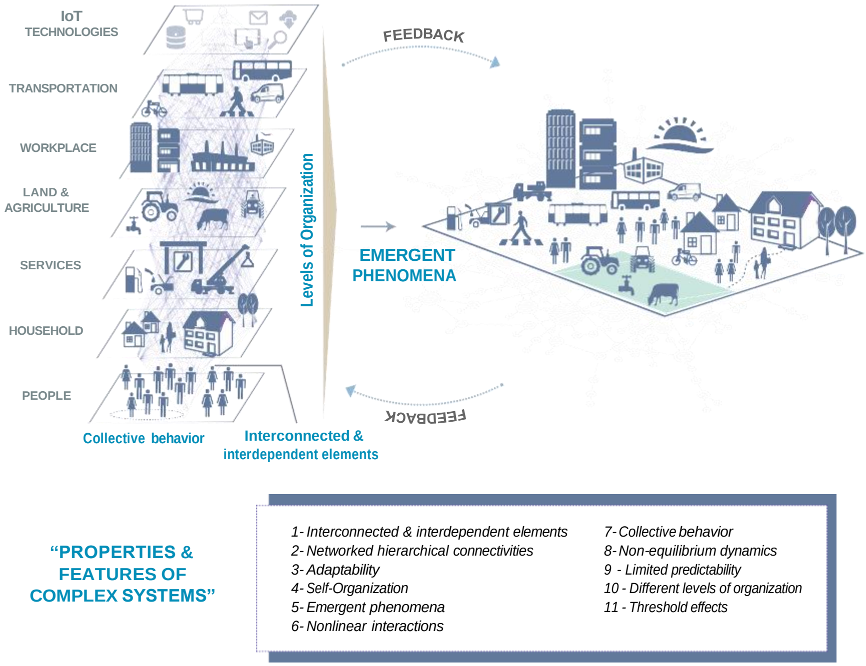

Fig. 1 A schematic of a complex system with continuous feedback between the interacting layers generating emergent phenomena: a city may be represented in terms of its different interacting layers (left), which give rise to emergent properties such as clusters of communities and traffic patterns (right). The properties and features of these types of systems are described in the adjacent box.

allow one to describe these evolving multi-level socio-ecological landscapes quite easily.

For example, 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. Networks also provide structures for the politics of coordination and cooperation. As a very specific example, we can study the relation between public/private transport when people maximise their own interest by reaching a sub-optimal general equilibrium in the city [78]. In general, networks in complex systems allow 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 [79, 80] work on managing the 'commons'. Cities are a true example of a socio-ecological system in the sense that Ostrom showed for the effective, sustainable management of the commons by institutions that arise in a self-organized manner from the interactions between individuals. Such institutions successfully (self-)govern the commons. To understand the system, the coupling between social institutions and ecosystem services must be considered. Note that this applies well beyond ecological or environmental questions, as commons arise in many other contexts, as in

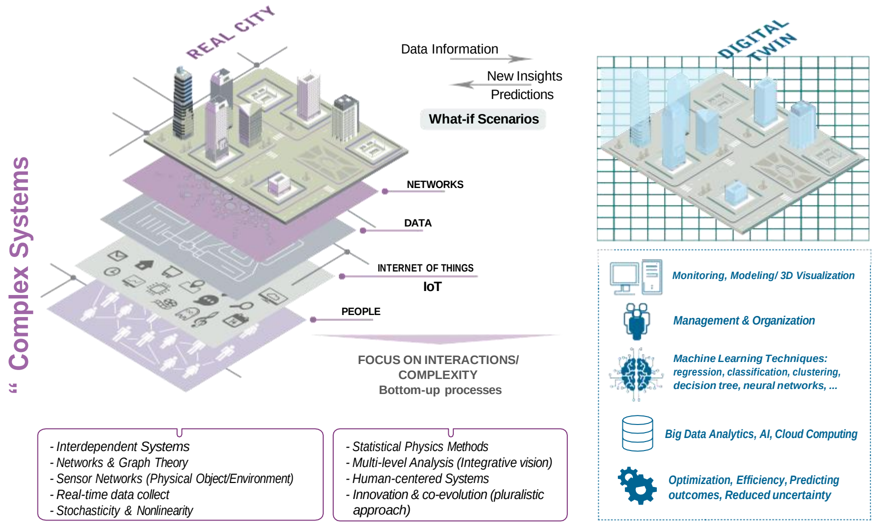

Fig. 2 (Left) The complex systems approach extracts selected information from a system's components and their relationships in order to simulate essential aspects of the system based on suitable simplifications, allowing one to understand collective dynamics resulting from bottom-up interactions. (bottom) 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.

questions involving urban energy, and pollution/air quality. It is then essential to identify the key drivers of urban problems, in order to develop strategies in line with resilience and sustainability goals [81] Networks allow us to focus on quantitative measurements such as the flow of energy in a specific area as in [82] where the author considers that the sustainability of a city is a complex, dissipative system [83] and must be assessed considering energy, material, and information flows. These exist at scales that offer an overall view, while at the same time giving insights into processes that determine how the city functions, i.e., how flows are transformed and efficiently used. These are intended to guide the world towards more equitable, livable and healthier cities.

Digital twins in complex systems can play an essential role in figuring out and illustrating how these diverse and widespread goals are interconnected and how they may be realised [84] Coupling digital twins with complex systems will also allow us to take into account bottom-up phenomena based on particular group behaviors and specialized zones that can be identified by specific parts of the network. This is particularly important in our rapidly changing world, which is determined by random noise, interactions, network cascades, and positive feedbacks. 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.

All these processes are created by multiple intertwined interactions between networks, developing at different levels and dimensions, that 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 the right interactions are in place, complexity provides a framework for decentralized learning built around systems of federated digital twins.

The kind of interactions we are referring to are all synergistic interactions, as opposed to those that generate friction. This requires the development of shared standards to ensure interoperability. It could also support the creation of hybrid systems (of humans interacting with smart technologies) that would boost collective intelligence and responsible collective action.

4 Challenges for integrating complexity science into digital twins

As implied throughout our argument, the data-driven approach represents a major leap forward with respect to previous frameworks. It is however insufficient to create an accurate model of our complex world, which is characterized by limits to theoretical predictability and practical control [85, 86].

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 Section 2). Surprisingly, less data or even noisy data can sometimes generate better models — and simpler models very often have more predictive power [87].

Working with one big data set that attempts to cover every known feature of the city, 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. The well-known problem of over-fitting plagues approaches that seek to extract patterns from big data using various kinds of machine learning techniques [88]. Very often, the focus is put on a detailed representation of the system's components, while their interactions are often a lot more important for understanding the behaviour of such complex systems [89]. Another relevant aspect is that we often lack data about interactions, so this inherently limits reproducibility, no matter how much data about the system's elements are available.

It would then be very important to add the interactions between the elementary components to include the fundamental foundations allowing one to understand and model cities better. Unfortunately, such interactions vary across different scales and range from human-human interactions to interactions between humans and the environment. It is thus necessary to study cities as ecosystems and also consider all living beings, not just humans, that compose them, along with machines and other systems. 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 thanks 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 as top-down intervention is never enough to explain and enable thriving cities. The focus, therefore, must be integrating bottom-up reactions which are central to an understanding of urban dynamics [90]. Similarly to living systems, cities evolve to generate morphology, networks, information, fabric, and functionality, which define the essence of their complex nature [91, 92].

Given the ambition for developing urban digital twins, they should reflect the behaviours and interactions of their actors, as cities are designed, built and planned by the people, for the people. This perspective corresponds to mapping many layers of complexity defining the city system [93–95]. 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 source of complexity, as human interactions lead to second and higher order phenomena [96], when people themselves detect the presence of emergent features and act accordingly. In addition, many time scales can be involved in these processes, which are crucial if a complex systems perspective is to improve the implementation of digital twins. One example of these features is the multiplicity of social norms [97] which can indeed lead to second order emergence [98], e.g., when the norm promotes cooperation and the adoption of some collective action [99, 100]. On the other hand, the dynamics of these feedback loops depend on both external as well as idiosyncratic factors, leading to a very complex dynamics, which take place over very different time scales [100]. A paradigmatic example is that of pedestrian route choice, a process involving information perception, information integration, and obstacle avoidance, all responding to information and decision making in context-dependent settings [101], which include personal cognitive maps . 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.

Moreover, digital twins require ethical norms and quality standards. 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 [88]. The fact that a city is composed of physical, biological, and social entities, should be addressed by digital twins reflecting all required details, taking the various known challenges into account [50] (see also 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.

Coupling network analysis to quantitative features such as proximity, success, and fragility, we may escape an approach focusing on optimisation and control by models of our system and empower civil society by taking into account bottom-up actions and activities [79]. Indeed, we must acknowledge that our digital twins may only be able to reproduce a small fraction of the relevant details of their real world counterparts. Thus, their predictability will always be limited. Therefore, we should consider structures and mechanisms that will allow urban systems to adapt by themselves, in spite of (or even taking advantage of) their inherent limited predictability. Actually, cities contain numerous legacies that are not simply the physical fabric of buildings and other material constructions, but cultures, histories, identities, values, symbols, and ways of life, far from being materialistic or physical in form. These should be included in terms of information flows that have a causal influence on the material and energetic flows within urban systems [82].

5 Summary, discussion and outlook: 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, in contrast to Chris Anderson's polemic a decade or more ago in 2008 [102]. Indeed, exactly the opposite has occurred. When it comes to dealing with bottom-up emergent behaviour which we need 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 far short in representing the complete set of relevant interactions between physical assets, processes, and systems. Complexity science addresses this problem.

Despite pervasive measurements at all scales, from satellites down to nanoscale sensors, building a fully-fledged 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 [103], and this implies ethical challenges [88]. At the same time, however, it opens up a way to learn from digital twins about bottom-up emergent processes. Human thinking, behaviours and materiality impact each other in complex ways that must be conceptualized through multi-layer systems of interaction networks.

Table 1 Pros and cons of the various approaches.

	Digital Twins	Complexity Theory
Realistic Data	✓	×
Community detection	×	✓
Failure prediction	×	✓
Interacting layers	×	✓
Validation	✓	×

How to manage such a system? Nature may inspire new solutions. Evolutionary algorithms can serve as inspirations to develop adaptive approaches to search for novel solutions. Nature adapts at multiple timescales, we can take inspiration from her recipes and algorithms, and apply them in urban contexts. Using the fastest (quantum) supercomputers, artificial evolution can to some extent be simulated, thereby allowing us to accelerate evolutionary time scales beyond the speed of cultural evolution. In such cases, we might consider the final equilibrium state as a possible suggestion as in the case of physical and informational flows in a city compared to living organisms[82, 83].

This may show us how to use local feedbacks in a way that empowers self-organizing, co-evolving systems. Again, this is achieved by taking into account quantitatively the bottom-up processes, the features, the behaviour of citizens in the way they aggregate and form the structure of the cities by means of networks. The way to achieve better planning of urban areas is not by working solely with digital twins but with combining them with complexity sciences.

The power of simulation enabled by digital twins must be used to realise "what if" scenarios. These are to be driven by a theoretical understanding of the phenomenon gained by collecting measurable quantities associated with intangible attributes that define how people function in cities.

Accordingly, a digital twin should be seen as one of the ingredients to bridge self-organization mechanisms and policy governance. Among the various objectives defining 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 policy makers and civil society at various levels to develop and progressively implement urban policies, providing participatory platforms for capacity-building activities.
- 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' [104] is a possible way forward.

We need platforms based on city structure to empower citizens and stakeholders by facilitating a participatory dialogue. We need to go beyond digital twins for cities requiring software that would function as a public "cyber"-space for community integration, where citizens can voice their opinions about proposed interventions, suggest changes, and point to problems. In this context, their combination with complex systems involving network analysis, phase transitions, and equilibrium analysis would promote participatory, collaborative explorations. These would be based on 'what-if' scenarios by citizens and local authorities, thus enabling policy-makers to make much more informed decisions [105].

Simulations are an essential tool for studying complex systems [106]. Thus, advances in traditional digital twins could also benefit the scientific study of complex systems, because they will identify classes of problem that can arise bottom-up and they can cluster together classes of results obtained from such simulations. This lies at the basis of our argument for urgent consideration of the complexity sciences while building and using urban digital twins.

In conclusion, as the processes of networking and urbanization in our globalized world evolve [107], we will increasingly face the key features, problems and opportunities of an increasingly complex world. When designed or operated without good insight and oversight, and without serious scientific validation, digital twins may generate serious concerns for their citizenry in terms of privacy and transparency [50]. However, if properly used and combined with complexity science and citizen participation, instruments like digital twins allow one to come up with adaptive, efficient, resilient, and sustainable solutions that are compatible with democracy, human rights, and innovation. Hence, when designed and operated effectively, digital models of the world (or certain aspects of it) can offer formidable policy instruments. This is not only so for the management of cities, but also for the co-evolution of many evidence and data-based information ecosystems, which can foster a new collaborative relationship between citizens and policy makers.

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