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Do urban digital twins need agents?

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Data Availability Statement included at the end of the article

Abstract
The urban digital twin (UDT) is derived from the original digital-twin concept of a representation of physical assets. This has left the social component of the city underrepresented in UDTs. Here, we discuss what this means for the current maturity stage of UDTs and why better representing human behaviour in UDTs may diversify possibilities to support different types of planning. We contemplate operationalizing the representation of human behaviour by means of agent-based models (ABMs) integrated with UDTs and illustrate this with two concrete examples of simulating stress and safety perception in public spaces. One example shows the idea of the UDT as a live data repository for ABMs, with the ABM adding dynamism, and the other of live feedback between the city, the ABM and UDT. We discuss several epistemological, conceptual, technical, and ethical challenges that may be involved in this integration. We conclude with a future agenda to promote (1) the abandonment of the vision of a UDT as *the* highly detailed mirror of the city, (2) UDTs fit for sectoral (strategic) in addition to operational planning, (3) the inclusion of behavioural and social processes in UDTs by incorporating ABMs, (4) a culture of cumulative research using structured guided frameworks and reusable building blocks, (5) ABMs with explicit purposes to allow fit-for-purpose selection in UDTs, and (6) explicitly addressing epistemic, normative, and moral responsibilities. Thus, though including agents may at some point be a solution for the (currently lacking) perspective on the role of humans in shaping and being shaped by the city, several reconsiderations in the UDT and ABM communities need to take place first.

Keywords
Digital twins, agency, urban-scale, modelling, agent-based modelling, psychological stress, spatial planning

Introduction

Cities around the world are densifying, placing pressure on urban public spaces (Buhaug and Urdal, 2013). These public spaces are crucial for fostering interaction and exchange between people and thereby impact the quality of the urban environment. Urban planning practices strive to provide citizens with positive experiences in public spaces (Mouratidis, 2021; Yang et al., 2024). In line with these efforts, the concept of urban digital twins (UDTs) has been introduced as a potential decision support tool for municipal authorities to monitor and plan public spaces (Charitonidou, 2022).

The UDT has emerged from the general digital twin (DT) concept, which is a 'virtual representation of physical assets' (Batty, 2018). This history has two main, interrelated consequences for the dialogue around UDTs. First, there is an ongoing discussion about the extent to which a representation of physical assets suffices to effectively aid authorities in decision-making. A definition of what a UDT should contain remains undecided, both at the conceptual level and in the technical specifications necessary to classify it as such. Second, present discussions predominantly emphasize the technical facets of digital twin cities, exemplified by the technologies needed to build the tool (Lehtola et al., 2022; Weil et al., 2023; Xia et al., 2022; Zhang et al., 2022) and interoperability between different systems (Quek et al., 2023; Raes et al., 2021a; Weil et al., 2023).

As a result, one of the unsettled and relatively unexplored issues in the UDT debate is the underrepresentation of the social components of cities in current UDTs (Ketzler et al., 2020; Lei et al., 2023; Weil et al., 2023). A solution would be to incorporate virtual citizens, that is, software agents that can intrinsically experience the digital environment and interact with it, as real citizens would do. We believe that failing to do so is a shortcoming of current UDTs; it is essential to recognize that cities are hybrid socio-technical systems. This means that they are not only composed of physical assets but also shaped by social factors, including cultural meaning, (spatial) cognition, social interactions, and governance structures, among others (Elzen et al., 2004).

In turn, these factors are also shaped by the cities themselves. For example, human health is closely related to experiences of the built environment. Studies have found that these experiences and perceptions can immediately influence human's physiological and psychological states such as stress, perceived safety, and cognition (Krabbendam et al., 2021). Evidence has shown that low-quality environments (e.g. environmental elements that trigger a sense of disorder, unsafety) elicit negative responses in individuals, such as stress and concern (Evans, 2003). In contrast, environmental elements, such as greenery, have been shown to contribute to positive emotion generation and stress recovery, and therefore to positive experiences (Li and Sullivan, 2016; Yang et al., 2024). Thus, when planning interventions in the built environment, it is not sufficient to solely consider physical elements; public space holds social significance, influences community well-being, fosters social interactions, and can support or hinder mental health. The example of mental health will serve as a case for the illustration of the arguments in this paper. A UDT that models cities purely as physical entities misses the social, psychological and ecological functions these environments serve.

As such, one of the presumed advantages of DTs, to explore and assess the socio-economic and socio-ecological impacts of proposed actions and changes in the environment (Bauer et al., 2024), is lost. We argue that integrating social entities and processes in UDTs would allow for assessing how citizens use public spaces and respond to possible urban design scenarios and how this affects these citizens. But how could the shift towards UDTs with a social component take shape? Could Agent-Based Models (ABMs) offer a potential solution? To address these questions, in light of the complexity of the city, we believe that an interdisciplinary discussion is necessary. Therefore, this article is written with and includes the viewpoints of scholars from various domains, including psychology, computer science, geography, health science, data science, and urban planning.

In the upcoming sections, we will first discuss the different perspectives on the UDTs as found in literature as well as articulated by practitioners in the Netherlands. Second, we will further build our argument that UDTs lack the representation of human behaviour and contemplate the use of agent-based modelling as a means to integrate human representation into UDTs. Third, we will elaborate on two additional ways in which ABMs and UDTs add value to each other: (1) UDTs can serve as a live data repository for ABMs and ABMs add dynamism to UDTs and (2) live feedback between ABMs and UDTs can take place. Both sections will provide examples of how agent-based modelling could be integrated into a UDT to clarify our arguments. Next, we delve into the epistemological, conceptual, technical, and ethical challenges related to integrating ABMs into UDTs. We conclude with the discussion of a future agenda.

Urban digital twin: diverse perspectives on its concept

Perspectives in literature

The concept of DTs gained popularity in the early 2000s with the advent of digitizing machinery and production systems in the manufacturing industry. The term was first presented in a lecture on product life-cycle management at the University of Michigan by Michael Grieves in 2003. Grieves (2014) attributed the term to John Vickers of NASA, with whom he had worked closely.

In his whitepaper 'Digital Twin: Manufacturing Excellence through Virtual Factory Replication', Grieves (2014) defines digital twin as 'a virtual representation of what has been produced'. According to him, the Digital Twin concept model is composed of three main parts: (1) physical products in real space, (2) virtual products in virtual space, and (3) the connections of data and information that tie the virtual and real products together.

Since then, the use of DTs has expanded into various domains, including medicine (Björnsson et al., 2020), supply chain analysis (Kamble et al., 2022), construction (Opoku et al., 2021), earth-system science (Bauer et al., 2024; Saltelli et al., 2024), biodiversity (Westerlaken, 2024), and energy science (Yu et al., 2022), extending to urban-scale digital twins. When it comes to cities, however, their digital representation is more complicated than that of manufactured products due to the inherent complexity of a city, as argued by Mylonas et al. (2021). Cities, as opposed to manufactured products, grow, change, and continuously transform themselves together with, and with impact on, their citizens (White et al., 2015). This makes it harder to decide what should be included in a UDT.

As a consequence, there is no consensus on what a UDT precisely is. Many authors use the original definition of digital twins and understand a UDT solely as a (3D) digital representation of the assets in a city (see, e.g. Shi et al., 2023; Lehner and Dorffner, 2020; Bellini et al., 2023; Deng et al., 2021; White et al., 2021; Weil et al., 2023). Shi et al. (2023) define it as 'a one-to-one corresponding three-dimensional (3D) representation of the real city'. In the perspective of Deng et al. (2021), a UDT entails 'collecting digital twins of city entities through digital twin technologies'. Some take into account the temporal dynamics of the assets; for example, White et al. (2021) state that 'an ideal digital twin would be identical to its physical counter-part and have a complete, real-time dataset of all information on the object/system'.

Some of the above are 3D visualisations of cities that offer nothing substantially beyond visualisation (Masoumi et al., 2023), but are still called 'Urban Digital Twins' by their creators and users. Such examples may incorporate analyses and calculations made using other means such as external geographic information systems (GIS), and they may offer interactive visualisation in forms such as adjustable timelines, animation, or layer and symbol toggling, but in these respects they are equivalent to the interactive cartographic and visualisation products of non-UDT technologies (Robinson et al., 2023).

Few authors explicitly see models as part of a UDT, mostly in the sense of data models rather than simulation models. For instance, Deren et al. (2021) state, 'It is generally believed that the "Digital Twin" is a simulation process that makes full use of physical models, sensors, historical data of operation, etc. To integrate information of multi-discipline, multi-physical quantities, multi-scale, and multi-probability', though they do not provide evidence for this general belief. If simulation models are mentioned in the context of a UDT, they typically simulate physical processes, such as floods (Deren et al., 2021), wind (Dembski et al., 2020), ground water tables (Koeva et al., 2023), and urban heat island effects (Cárdenas et al., 2023). Dembski et al. (2020) also include a simulation of traffic, and Cárdenas et al. (2023) quantify the human perception of thermal conditions in their urban heat island computation, showing that a start has been made to include human behaviour in UDTs, though at an aggregate level.

More recently, some authors have been raising the need to incorporate more complex aspects of the city in UDTs. El Saddik (2018) acknowledges that physical 'assets' of a city should be interpreted as physical entities, which could thus include individual humans, with 'AI' providing intelligent decisions. Nochta et al. (2021) argue that the conceptualization of UDT needs further refinement, utilizing interdisciplinary insights from both the physical and social sciences.

Perspectives in practice

As the above analysis provides an academic view on UDTs but no perspective on how and for what purpose UDTs are used in practice, we performed interviews with employees from four municipalities in the Netherlands, who were responsible for UDTs as part of their portfolio. Each interview took one to two hours. The interview questions and selected parts of the answers can be found in Appendix A. Follow-up questions were asked depending on the answers and questions not relevant anymore in the light of previous answers were skipped. We do not disclose the names of the municipalities (1) to preserve the anonymity of the interviewees and (2) because the view of the employee does not necessarily reflect the view of the municipality as a whole. Nonetheless, the answers give insight in diverse perspectives that exist among those that work or plan to work with UDT in an everyday context.

The group of practitioners was found to hold two different views on the purpose a UDT should serve. One the one hand, three of the four interviewees indicated that they built UDTs to answer *specific* questions about the cities. That is, the UDT is used as a tool that supports decision-making in relation to a particular issue. For example, in one of these three municipalities a dedicated-purpose UDT is being developed to support the decision of where to build houses in the coming decades in the context of city policies. The twin can, for example, be used to test whether different design scenarios adhere to the policy goal to add eight square metres of greenery in the city to each house. Using the UDT and its dashboard, the policy makers can identify under which scenario(s) the goals are met. We call this *purpose-specific* UDT development.

One of the interviewees, on the other hand, had a different approach to building UDTs. To them, a UDT is not a question-driven tool, but rather a data concept. The first step in the development is therefore the creation of a more general open urban platform with a digital representation of the *entire* city. This open urban platform serves as a versatile infrastructure to connect multiple data sources and tools, enabling the testing of multiple questions about different areas and their interactions. The UDT involves establishing rules for this infrastructure, particularly concerning data standardization, to ensure a common and shareable view of the city's physical situation. We call this *general-purpose* UDT development.

In other words, practitioners all have a focus on the technical aspects of UDTs, but differ in whether they build a UDT as a custom-developed, dedicated tool for answering specific policy questions, or as a more general-purpose data platform. In this context, it should be noted that some of the cities that build purpose-specific UDTs mentioned having the ambition to build a general-purpose platform that gathers and connects various data (see Appendix A), but that this is not how they currently operate. Yet, all refer to their use case as a digital twin. Please note that these views are only a sample of perspectives in the Netherlands and are not necessarily generalizable to the rest of the Netherlands, let alone the rest of the world.

Our perspective on the current status of UDTs and the consequence for urban planning

From the previous two sections, we can conclude that what people currently call a UDT is a digital representation of the assets in a city with the technical infrastructure and 3D spatial data models to store and visualize these assets. UDTs are intended to be general-purpose analytical tools, though they currently are typically operational for only single case studies. Consequently, in the remainder of this paper we refer to UDTs as they are used currently in practice, namely, as *a digital representation of the assets in a city including the technical infrastructure and 3D spatial data models, intended to have a general purpose*.

According to the Digital Twin Maturity Model (Kogut, 2022; Raes et al., 2021b), developed by DUET (Digital Urban European Twins) (Figure 1), this puts current UDTs at the level of *Experimental twins*. That is, current UDTs bring together a small number of structured urban datasets for a specific use case, which supports decision-making based on historical data.

For decision-making, this means that UDTs are currently best suited for operational planning. UDTs are supposed to help with the integration of various mono-disciplinary (Batty, 2018) or the so-called sectoral (strategic) planning and policy-making endeavours (Witte and Hartmann, 2022), but currently do not achieve this goal. To move to UDTs useful for sectoral, and thus for long term, planning we do *not* need evermore accurate geospatial representations or maps of the reality in 3D. Instead, we need (simple) models that help decision-makers better understand the inter-causal effects resulting from the nexus of sectoral policies, plans, or design interventions on multiple outcomes of interests or policy goals. This includes understanding how such interventions are likely to influence the behavioural and social patterns of users.

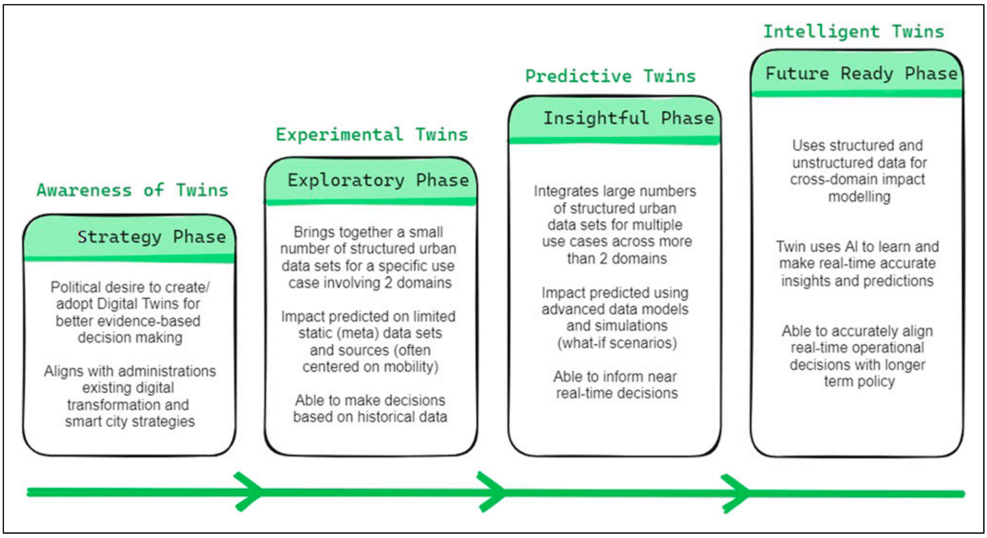

Figure 1. Digital Twin Maturity Model proposed by DUET, adapted from Kogut (2022).

Building upon the DUET framework (Figure 1), we argue that, to support sectoral planning, a UDT should have at least the Predictive Twins level but ideally the Intelligent Twin level, as a starting point. As such, further simulation modelling capabilities – such as those provided by ABMs – are required of a UDT, and they should include human entities, as argued in the introduction.

Humans are lacking in the digital city. How can they be represented?

Agent-based modelling of urban systems

To achieve the Predictive Twins level for UDTs, it is necessary to include not only the static, physical assets of a city but also the moving and dynamic entities such as vehicles and citizens that represent the behavioural and social processes in a city. Behavioural and social processes by citizens are the main drivers of the complex dynamics that characterise cities; as such, a city can be seen as what is often denoted as a coupled socio-technical or socio-ecological system (Filatova et al., 2013; Frank et al., 2017). However, current UDT efforts lack a representation of the 'socio' component.

Agent-based modelling is a simulation modelling paradigm that enables the representation of social behaviour by defining agents representing social entities (Crooks and Heppenstall, 2012; Gilbert, 2020; Schlüter et al., 2017). Agents (A) are computational entities that are immersed in an environment (E), perceive their environment and other agents, and, based on that, generate a behaviour that might change their environment, the agent itself or other agents. The environment consists, in this case, of the physical assets of the city such as infrastructure, green area, or buildings. The interactions mainly refer to:

- The perceptions a human agent has about its environment ($E \rightarrow A$);
- The interactions between the environment and a human agent which involves the adaptation of the environment by the actors in the pursue of their objectives ($A \rightarrow E$); and
- The interactions between human agents which include aspects like communication, negotiation, and collaborations ($A \rightarrow A$).

ABMs can have several benefits for modelling socio-technical systems (Bonabeau, 2002) over approaches that model the system at an aggregate level, such as differential equations. Firstly, representing behaviour at the level of an individual is intuitive because this is the level at which we ourselves operate, and thus easily relate to. Secondly, modelling each individual separately allows modelling feedback between individuals, path-dependence, and hysteresis effects. Thirdly, it allows for embodying heterogeneity in the population, which is crucial as the heterogeneity in combination with feedback may lead to processes like group formation or polarisation (Siedlecki et al., 2016).

An ABM can simulate the mechanisms that drive urban systems, thereby offering insights into how changes in one area can ripple through to affect the state of the entire system. Even though quite challenging, agent-based modelling stands out as a particularly effective method for building causal models of urban environments (Bonabeau, 2002; Crooks et al., 2008). ABMs replicate the actions and interactions of individual agents (which can represent people, vehicles, institutions, etc.) within a virtual environment to observe emergent patterns over time. This bottom-up approach to modelling allows for the exploration of complex scenarios and the examination of potential outcomes of various policy interventions (what-if scenarios) (Crooks et al., 2008), thus fitting the ambition to move to Predictive or Intelligent Twins for long-term urban planning and decision-making (Figure 1).

Much of the power of ABMs comes from their ability to discover or explain how processes or behaviour at one phenomenon scale (Montello, 2015) give rise to effects or further processes at another scale. The scale at which agents exist and operate drives the emergent patterns seen at the scale of the environment or collective of agents. UDTs, in contrast, are thought to be most useful at some singular, high-fidelity modelling scale. With modelling and interactivity, both are ultimately about observing the collective patterns affected by micro-level components of the model. If, for example, a UDT can model municipal electrical consumption, it is because it contains smaller elements, such as households, that each consume energy. Whether or not the UDT in this example explicitly models its houses in an object-oriented method, the households each have individual effects that culminate together into a macro pattern, and are thus potentially behaving as agents in an ABM. This makes UDTs a good fit with ABMs, as opposed to model paradigms that simulate the macro pattern directly (cf. differential equations).

ABM as causal model for informative UDTs

The formulation of policies in urban planning has increasingly leveraged the power of digital technologies to foster healthier, more sustainable cities. While recent years have seen the emergence of so-called data-driven urbanism (Kitchin, 2017), we maintain that urban geographers, planners, and policy makers should not overlook the explanatory power of ABMs as causal models. In fact, agent-based modelling emerged as a generative science aimed at contributing to theory building and hypothesis testing, and thereby providing insights on the mechanisms and dynamics that regulate the simulated system (Epstein, 2012). ABMs are traditionally built on the formalisation of particular theories or frameworks (Bianchi and Squazzoni, 2015; Epstein, 1999). As such, the model rules represent (assumed) *causal* relations, which can also be applied when data about a certain phenomenon is scarce.

Around twenty years ago, modellers across different disciplines started emphasising the necessity of developing data-driven ABMs (Boero and Squazzoni, 2005) (see Jager and Ernst, 2017; O'Sullivan et al., 2016, for a discussion on these themes). While the call for the inclusion of data in agent-based modelling was mainly an appeal to better calibrate, validate, and generalise models (Janssen and Ostrom, 2006; Rounsevell et al., 2012; Smajgl et al., 2011), some have built agent mechanisms entirely based on correlations in data instead of causation in theories (for a review: Smajgl and Barreteau, 2014). This is what we refer to as data-driven ABMs, models in which aggregated data – for example, trajectory data about people moving in a city by car – guide the definition of the agent behavioural rules or mechanisms in the ABM. Despite their dissemination, these models primarily offer predictive insights (Taghikhah et al., 2021) whose value is inherently tied to data quality and availability, and built on evidence that is 'already' in the past and not necessarily representative for the future; they lack interpretability and interoperability (Lorscheid et al., 2019), and they hinder the adoption of common structures across the community (Berger et al., 2024; Hauke et al., 2020).

Moreover, causal ABMs have been described as more suitable than data-driven ABMs when it comes to account for emergent behaviours and non-linear dynamics (Lorscheid et al., 2019) that characterise urban an systems (Crooks and Heppenstall, 2012). As some psychologists (e.g. Smaldino et al., 2015; Smith and Conrey, 2007) have moved their experiments away from their laboratories and turned to agent-based modelling, the challenges of simulating human behaviour across urban space still calls for a deep 'theoretical engagement' (O'Sullivan et al., 2016). Not only should the modelling community refer to theoretical frameworks about urban space (the system) and human behaviour (agents), but it should also strive to develop new theories regarding how macro-level patterns may arise from certain behavioural components (see also next section).

For example, one could build a causal ABM of residential choice on the *Filtering Theory* (Gray and Boddy, 1979), which posits that, as tenements age and deteriorate over time, they 'filter' down to lower income occupants. The agent behaviour in this model could emerge from the interaction between the agents' income and buildings' characteristics. Additional components derived from theories in (social) psychology could be included to investigate how these elements together bring up different (or more plausible) residential mobility patterns. The model could be further calibrated or validated with data about residential mobility. However, a data-driven ABM exclusively based on correlations across said data about residential mobility and variables in a census dataset, for example, in 2013 could be suitable for making static predictions or analysis, but would not been able to provide reusable and scalable scientific insights into the dynamics of the phenomenon (Epstein, 2008; Lorscheid et al., 2019). On the contrary, the causal model could be applied to other urban contexts, used to explore how the population may react to certain interventions (e.g. building retrofitting), or to refine the filtering theory.

When we advocate for a more robust integration of agent-based modelling in urban policy making, and, to some extent, in the design of UDTs as more informative rather than purely visual tools, we refer to a committed shift (back) to causal ABMs that have the strength to provide reliable projections of the long-term implications of policy interventions and thus value for sectoral planning (O'Sullivan and Perry, 2013; Pearl, 2009).

Agent architectures

By definition, agents exhibit autonomy, meaning that they can operate without direct intervention of a central controller (Bonabeau, 2002). Therefore, they should possess social abilities, meaning that they should be able to interact with other agents. A common way to model agent architectures is as a reactive agent architecture, in which the cognitive capacities of agents are limited to perceiving their environment and reacting on it in a predefined way (i.e., action-reaction, or selection rules). More advanced architectures try to get even more of the internal (cognitive) processes of the agent captured by the model. This can include defining a proactive agent, wherein agents not only react but also exhibit goal-directed and deliberate behaviour (Gilbert, 2020).

Among these more advanced architectures, there are various frameworks and levels of abstraction for how to model a human agent. One specific area from which inspiration can be taken is cognitive architectures. Cognitive architectures aim to capture the general principles that describe and regulate human behaviour in a single framework, at such a level that computer code can execute that behaviour in specific tasks (see also Anderson, 2007; Newell, 1990). Cognitive architectures distinguish between the core 'architecture' of the human mind – the general principles that guide behaviour (e.g. how does memory work in general? How do eye movements work?) – and task-specific models (e.g. how is memory used in a specific setting). This distinction between core architecture and specific models is useful in the context of UDTs, where a general-purpose twin might specify generic principles of behaviour (following the architecture), yet make tweaks to specific settings. By now, there is a wide variety of cognitive architectures and models inspired by those to choose from (Oulasvirta, 2019), and there are many other detailed models of cognition that go even deeper on specific elements (see e.g. Kriegeskorte and Douglas, 2018), or specific application domains, such as transportation (Janssen et al., 2022, 2024).

As there is a wide variety of frameworks possible to inform the design of agent architectures, a point of attention is at what time scale the human (cognitive) processes should be defined. Insights from the field of learning and education suggest that specification of processes in the order of multiple seconds – as is common in agent-based models can be useful. Specifically, Anderson (2002) reviews evidence from the field of learning that (1) learning that happens over longer time scales can be *decomposed* into learning over smaller timesteps, (2) such smaller timesteps are *relevant* for behaviour over longer time scales, and (3) that *modelling* these small steps is useful as it provides a formal way to trace behaviour over longer time-scales. For example, how one masters concepts in algebra over 100s of hours might be decomposed into how one practices smaller sums over 10s of seconds, and models can help to trace what types of equations go well. Similarly, in UDTs, behaviour that emerges over longer time scales (such as the flow of traffic) might be decomposed into smaller behaviours by individual agents (such as their route choices, how fast they move, whether they decide to stop; which in turn might be influenced by e.g. their goals and their perception of the world around them).

Anderson (2002) also indicates that, within the field of learning, the most successful models model behaviour in steps of up to 10 seconds ('unit task'), but models that model even smaller timesteps (10 milliseconds to 100 milliseconds) are also gaining momentum. In the context of UDTs, specifying human behaviour through agent based models in steps of 1 or more seconds therefore seems a fruitful starting point. In the context of UDTs, integrating such models would also require measuring human behaviour at such a level of detail that the measurements of the real world can be linked to the details in the 'twin' world. The exact specification and granularity might differ across applications.

The next two sections describe two concrete benefits we see in the integration of UDT and ABM: the UDT as a live data repository for ABMs, with ABM adding dynamism, and live feedback between the city, the ABM, and the UDT. These benefits are illustrated by two corresponding examples and their conceptual models, in which we show how human behaviour could be simulated in the integrated framework.

UDT as a live data repository for ABMs, with ABM adding dynamism

Citizens consistently engage with their immediate environment, whether it is through interactions with one another or with the physical environment around them. When considering the latter, in line with the ideas of Bellini et al. (2023), a UDT could serve as a live data repository for ABM that includes geospatial data acquired from diverse sources, such as earth observation and volunteered observation, (Huang et al., 2024) and traditional 2D and 3D GIS data layers provided by agencies. Regarding the data provision, we see two aspects as a way forward to leverage digital twinning for ABMs.

First, for agent-based modelling, an adequate depiction of the street-level environment and how it is perceived through the eyes of agents on the ground adds granularity (Helbich et al., 2021) to the ABM. For instance, integrating (open) street view imagery alongside deep learning approaches to exact visible features of the streetscape (e.g. cars, trees, and facades) appears to be a valuable addition to shaping agents' behaviour that can hardly be obtained through other means.

Second, agents add dynamism to UDTs. The backbone of contemporary digital twins is mainly concerned with static (or only slowly changing) environmental settings on a large scale (e.g. buildings, land use, and road networks). The aspiration of UDTs is to include highly dynamic data via sensor networks. These sensors, either positioned on buildings or mounted on mobile entities (e.g. public transport vehicles) (Goodchild, 2007), enable the measurement of specific dynamic conditions that change throughout the day, such as traffic conditions contributing to air pollution (Zhang and Woo, 2020). Such near real-time data could prove beneficial in-prompting adjustments to agents' behaviour (e.g. their route choice). The agents' interactions with the static and dynamic aspects show how the environment influences that state of these agents, which adds extra dynamism to the UDT, thereby depicting a more realistic socio-technical system.

An example to illustrate the UDT as data repository for the ABM

In line with the example presented in introduction, we explain how UDT data might be connected to an ABM of a student's stress level that may change while moving on the campus (Figure 2). For a student agent trying to reach a classroom on campus, the UDT of the surrounding environment is constantly serving as a repository of data that supports the agent's cognitive appraisal and behavioural choices throughout the process. Environmental stressors here might include crowds, noise, or difficulty of wayfinding (Beermann and Sieben, 2023; Kanakri et al., 2016). These stressors have the potential to contribute to chronic stress (Norgate et al., 2020). During the interaction between the agent and the UDT, data on the agent behaviour and stress levels are continuously collected and processed by the UDT.

In the ABM, there is one type of agent: a student. The student's stress level is included as an agent attribute that might change based on their interactions with other agents and the environment. The conceptualisation of stress could be derived from literature of from a survey asking students about their self-rated stress levels before and after navigating campus to class, or experience sampling through a dedicated app for phone and smartwatch, or by collecting biological samples (e.g. saliva) to measure cortisol levels (Van Holland et al., 2012).

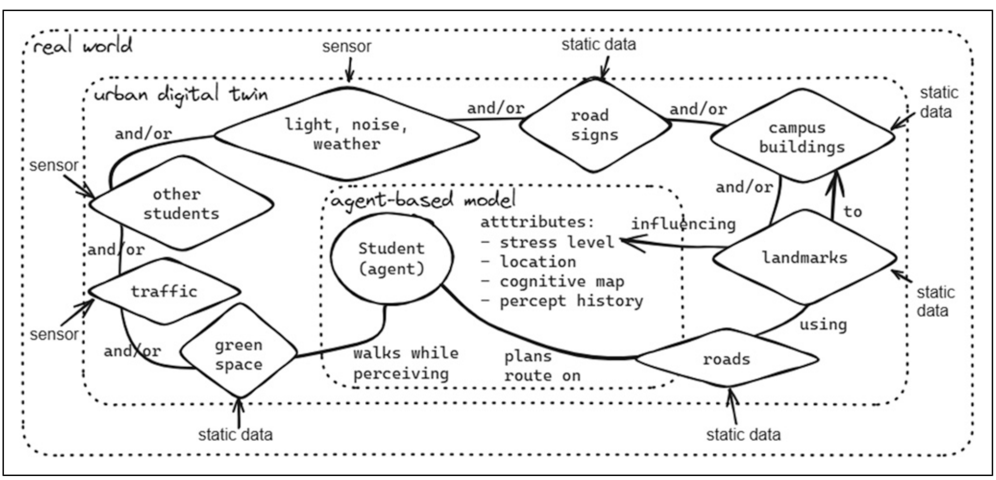

Figure 2. UDT as a live data repository for ABM: Agent-based model of a student's perceived stress while walking on campus to find a lecture hall, where the environment of the agent is provided with data (static or live) by the urban digital twin, which senses the real world.

The agent starts by selecting the destination and planning routes (Figure 2). Herein, the static data on campus buildings and roads are provided by the UDT and gradually form the agent's incomplete cognitive map of the campus. Furthermore, (naturally) dynamic data is measured in the real world, fed to the UDT, and then to the ABM. This includes the presence of other people on campus, light, noise and weather conditions, and traffic (Figure 2).

As the agent performs its wayfinding task, it experiences different levels of stress on the basis of the stressors encountered along the route. Having monitored changes in the agent's stress level, the UDT can dynamically connect it with the physical environment attributes in which the agent is currently surrounded by and further identify potential problems in the environment, such as a lack of clear signage and nearby green space that could help alleviate stress, or problematic traffic conditions.

Live feedback between the city, the ABM, and UDT

Following Grieves (2014), we consider the three elements of a UDT as (1) the city as a physical space, (2) its digital representation in the digital space, and (3) the data that connects these two spaces. The data exchange operates in a loop: information from the physical city feeds into the UDT, enabling analysis – such as through a dashboard – and decision-making, leading to interventions in the physical city (Deng et al., 2021). The planning of these interventions is communicated back to the physical space, through data, generating changes in the physical city (Schrotter and Hürzeler, 2020). These changes, then, are fed back into the UDT, and so forth.

An ABM can be plugged in within this loop. It is integrated in the UDT, just like in the previous section, but now it becomes part of the feedback with the city. Thus, the agents respond not only to static and (naturally) dynamic features in the environment, but also to interventions, that is, actuated dynamics in the real world (Figure 3).

Inevitably, the modelled system in the UDT and the observed one in the city will diverge over time. There are two potential solutions to this problem. The first solution is to try to avoid divergence by not having a one-to-one mapping between agents and actual people. We could let the agent(s) that we monitor in the model be entities that do not have a real-world counterpart. Such agents would

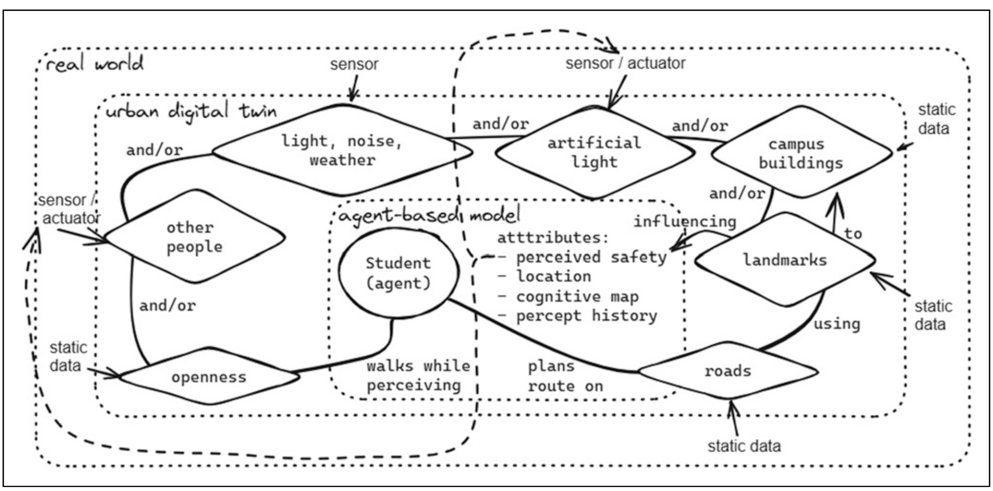

Figure 3. UDT as a way to provide live feedback between the city and the ABM: Agent-based model of a student's perceived safety while walking on a campus where the university changes outdoor lighting, where the environment of the agent is provided with data (static or live and actuated) by the urban digital twin, which senses the real world.

serve as inspectors to get a sense of the circumstances in their surroundings (consisting of objects and agents that do have a real-world counterpart, detected by sensors). The well-being of the inspector-agent would help to decide if interventions are desired. Such solution could only work if the inspector-agent does not (or barely) influence the behaviour of the agents around it; similar to how agent-based modelling is applied in hydrology to follow the flow path of the water and report on it but not determine it (Reaney, 2008). For example, it would not work if the inspector-agent can start a riot.

The second solution to try to solve the divergence between UDT and the observed city when it occurs. This can be done by means of data assimilation, a set of methods to combine model and observations to obtain a more realistic model state (Carrassi et al., 2018). The rationale behind data assimilation is to exploit the respective informational content of model and observations, where the model has a large spatial and temporal coverage but low accuracy, while the observations have a low spatial and temporal coverage (only at the locations of sensors) but a high accuracy. Data assimilation is already performed in near-real time in weather forecasts (Lean et al., 2021). It has been incidentally applied to models of socio-technical systems (e.g. Suchak et al., 2024; Ternes et al., 2022; Verstegen et al., 2014), but, to the best of our knowledge, never in (near-)real time, a challenge also recognized by others (e.g. Swarup and Mortveit, 2020).

An example to illustrate live feedback between the city, UDT, and ABM

Our example to demonstrate this feedback loop revolves around an intervention whereby the university intends to decrease the levels of the outdoor lighting on campus after dark, for cost or energy efficiency reasons or in an attempt to decrease light pollution for nocturnal wildlife (Figure 3). An ABM could allow the prediction or projection of changes in students' behaviours and perceptions as they relate to crime and safety in response to that intervention.

Agent-based modelling is well suited to modelling perceived safety as it depends on individual characteristics, as well as interactions with both the environment and other people therein. Indeed, individuals first have a base level of perceived vulnerability that affects their sense of safety in ambiguous situations. This can be estimated through some objective variables such as age, gender, and identification with a minority groups; and some more subjective such as personal history and previous experience, but also familiarity with the campus itself. Secondly, spatial characteristics of the environment such as openness, and sense of prospect and refuge (Appleton, 1975) can affect perceived safety by providing people with the opportunity to 'see without being seen'.

Interactions with other people also influence perceived safety through, for example, the concept of 'eyes on the street' proposed by Jacobs (1961) whereby the presence of people nearby instills a sense of security. However, the presence of people can also be seen as a threat depending on whether they are perceived as potential defenders or attackers (Appleton, 1975; Lis et al., 2024). This perception depends on the individual levels of perceived vulnerability as well as socio-demographic indicators, behaviours and the location in which the encounter takes place. In all cases, the decrease of outdoor lighting will affect visibility and, in turn, the sense of prospect, increases the likelihood of perceiving others as potentially threatening and, finally, affect the perceived safety.

Several types of agents could be introduced in the model: students, security agents patrolling the campus, and potential offenders. Students' perceived safety is recorded as an agent attribute, alongside their schedule and routine behaviours. A UDT of the campus is populated with campus buildings including typical destinations (dorms, cafeterias, etc), roads, areas of both prospect (high visibility and openness), or refuge (no visibility, enclosed space) identified through a spatial survey (Figure 3). Weather conditions, seasonal rhythms, and time of day would also be integrated as they influence behaviours and visibility. The model could then run, while agents dynamically record their perception of safety, based on changes in the environment, interactions with other agents, and personal experiences. Besides these static and naturally dynamic environmental features, there would be features that can be changed through interventions, such as artificial lighting points and other people (the security agents).

Sensors placed on campus could record real-time lighting levels, number of people (including people from security), and potential incidents. Through the feedback between real world, UDT and ABM, problematic areas could be immediately identified and the lighting, and potentially security patrol, adjusted accordingly. In this way, the intervention could be modulated for different locations around campus or weather conditions, thereby maintaining students' perceived safety, ultimately reducing student stress levels.

Epistemological challenges

Though the previous arguments and examples highlight gains for UDTs integrating ABMs, it is important to carefully consider the compatibility of the two concepts. Epistemologically and etymologically, the two terms do not immediately match. The term digital twin points towards the goal of making a digital representation that mirrors the real world (in our case the city) as well as possible in large detail. 'An ideal digital twin would be identical to its physical counter-part and have a complete, real-time dataset of all information on the object/system' (White et al., 2021). Even though some recognize that this is 'an idealization that will never be achieved' (Batty, 2018), this mirroring ideal remains the core concept of UDTs.

In contrast, a model is defined as a simplification of a certain object, phenomenon or system with a specific thematic focus. Herein, this simplification depends on this focus, that is, the model is more detailed in its central ideas and less detailed or more abstracted in the parts of the object/phenomenon/system that are considered irrelevant for the given focus (McClelland, 2009). For example, an ABM of route-choice behaviour of pedestrians in a city is detailed in how the pedestrian picks one street over another, as the other would lead to a different route, but does not specify whether the pedestrian is on the left or right sidewalk of that street (Filomena et al., 2022).

In terms of purposes, there also may be a mismatch between UDTs and ABMs. Though many people mainly think of ABMs (or models in general) as a means to predict the future, prediction is only one of the possible reasons to model (Epstein, 2008) and the term prediction is often used erroneously (Verstegen and Scheider, 2023). Models, and ABMs in particular, are used more often to explain, describe, or stimulate dialogue (Edmonds et al., 2019; Epstein, 2008). As Epstein (2008) puts it, modelling is making an implicit set of ideas into an explicit explanation or description that can be discussed; however these ideas do not necessarily reflect reality, as a UDT aims to do. Another common purpose of ABMs is to project, entailing an 'if-then' (or conditional) statement, for example, to evaluate effects of a potential intervention in the system (Verstegen and Scheider, 2023). A potential intervention is not there yet by definition and also not necessarily expected to be (as would be the case with a prediction), that is, not a twin. Thus, besides the central thematic focus (above), the modelling purpose too acts as a kind of filter (Edmonds et al., 2019) that often shifts ABMs away even more from being an accurate representation as in the ideal twin concept coming from manufacturing field.

Finally, even when prediction is the purpose, if both the environment and the agents are required to be fully realistic, this purpose demands '[…] modelling a highly complex, dynamic spatial environment, compounded by the problems of modelling highly complex, dynamic decision making units interacting with that environment and among themselves in highly complex, dynamic ways' (Couclelis, 2001). If possible at all, the costs of the added dimensions of complexity in models are by many considered to not exceed the benefits (Couclelis, 2001; McClelland, 2009).

Does the epistemological mismatch between ABMs and UDTs imply that the two should not be integrated? Or rather that one of the two should revise its epistemological foundations first? Along with authors from recent publications in the fields of earth system science (Saltelli et al., 2024) and biodiversity (Westerlaken, 2024), we argue that it is the DT epistemology that requires revision. It is problematic to present a single view of the world that is based solemnly on what can captured by technology, that is, by data (Westerlaken, 2024). And, according to Saltelli et al. (2024), DTs of the earth express a reductionist view that is philosophically untenable. They consider the wish to make highly detailed digital mirror of the world an old trap, as illustrated by their examples of the fictional stories of (Saltelli et al. (2024), Carroll, 1893, in: Saltelli et al. (2024)) and (Saltelli et al. (2024), Borges, 1998, in: Saltelli et al. (2024)) about nations whose maps became so detailed and large as the territory itself that they were considered useless and forgotten. In line with these arguments, we call for UDTs to include a wider and less data-driven range of perspectives instead of a single, detailed mirror.

Conceptual challenges

The agent-based modelling community has shown a propensity to 'reinvent the wheel' by adopting varied terminology for analogous concepts (Achter et al., 2024). This was likely unavoidable because similar ideas developed in different domains in similar periods (e.g. individual-based modelling in ecology and multi-agent systems in computer science). Remarkable efforts towards standardisation, interoperability, replicability, and communication (Grimm and Railsback, 2012; Hauke et al., 2020; Manson et al., 2020) have been recently made, but challenges remain: modellers struggle with incorporating and generalising knowledge from existing models into the ones they are developing (Achter et al., 2024). This is particularly the case for ABMs of socio-technical systems and for specifications regarding human behaviour and decision-making processes. The latter are often simplistic, contradictory, poorly detailed (Berger et al., 2024; Wijermans et al., 2023), or based on different operationalizations of the same theory. For instance, the well-known theory of planned behaviour (Ajzen, 1991) has seen a multitude of divergent formulations in agent-based modelling (Groeneveld et al., 2017). As one considers that most of the theories on human behaviour adopted in the social simulation community have been borrowed from economics (Groeneveld et al., 2017), modellers should not only embrace more transparent research practices but also revitalise the relationship with 'theoretically and/or empirically working scientists' (Groeneveld et al., 2017: p. 40) in (environmental) psychology to better substantiate their assumptions. Without this, the models will not find their way into UDTs.

Another challenge is how to balance the level of detail (in terms of processes/behaviour as well as space and time) that is needed for model specification with the more high-level abstraction with which model outcomes need to be represented to be practically useful. All models are an abstraction from reality, to ensure they address the core scientific of practical issues at hand (McClelland, 2009). To be scientifically sound, sufficient details should be in there. For example, to capture individual differences between agents, some parameters need to be included that capture that heterogeneity. However, in the application of a twin, for example to predict traffic streams, a representation of more high-level behaviour is needed. Representing that with all details on individual differences might distract from identifying the more higher-level predictions the model makes. For example, policy makers might be more interested in predictions about traffic streams, or likelihood of accidents. Yet they should be confident that the underlying model assumptions are correct, and be able to investigate those in more detail when needed. It is a scientific challenge to balance the rigour and details of a model with its ability to communicate more high-level outcomes. This challenge is present in ABMs in general, but becomes more pronounced in UDTs, as UDTs are more decision-support focused.

Technical challenges

Some claim that the development of social model components in UDTs is less constrained by technical challenges and more by the lack of our ability to understand and generalise such systems (Bauer et al., 2024). Still, there are a number of technical challenges that limit the integration of dynamic models in general (i.e. not only ABMs) into UDTs. The first is the matching of spatial and temporal extents and resolutions (discretisations) of different existing dynamic models. The processes that influence an individual's behaviour might play at the millisecond level, whereas the change in, for example, traffic conditions or level of building maintenance might occur over minutes, hours, or weeks. Correspondingly, models that have been built to simulate these processes will differ in their spatial and temporal extents and resolutions. Therefore, connections between models or model components may need to be made that they can span several orders of magnitude (Anderson, 2002). Solutions have been proposed for resolving misalignment between simulation models, for example, with accumulators as building blocks (Schmitz et al., 2014), but to the best of our knowledge such solutions are currently not implemented in UDTs. Furthermore, if the feedback between the city, the ABM and UDT really needs to be 'live', the ABM has to be fast enough to be run in real-time, thus matching exactly the processes operating the real system. Although it is unlikely to have a system without any time-lag, the lag may be short enough to enable timely actions or interventions in the city (Batty, 2018).

Second, the matching between model components does not only need to happen at the data and process flow level, as described above, but also at the semantic level (Argent, 2004). If a model requires daily temperature as an input and a dataset available in the DT provides daily temperature, this seems a fit; the data can be used as model input. Yet, upon further inspection, the two daily temperatures may have different meanings. Is it the temperature averaged over the day from sunrise until sunset, over the day from midnight to midnight, or over the day from noon to noon (as meteorologists tend to do)? Such problems of semantic interoperability may occur between data and model or between different models at the level of model concepts, observations, and context, and could be (partially) solved through semantic annotation (Villa et al., 2017).

Ethical challenges

The concept of UDTs, already now at the Experimental Twin level but even more so at the Predictive or Intelligent Twin level (Figure 1) when they include ABMs, leverages extensive datasets sourced from human behaviour. These datasets may include individuals' movements, activities, and preferences. These, alongside the mathematical models and algorithms, transcend a mere technological artefact due to UDTs' aim to support (political) decision-making on societal problems. Positioned at the intersection of technology and society, UDT and the potential combination of it with ABMs emerge as a socio-technological construct that can affect and be affected by power dynamics involving humans, society, and decision-makers (Nochta et al., 2021). Consequently, this can give rise to ethical and privacy-related concerns, including issues related to power asymmetry, data quality and control, and transparency and accountability. For instance, the use of vast amounts of data raises concerns about the protection of personal privacy (Shahat et al., 2021). Moreover, ethical concerns arise regarding the risk of misrepresenting or inaccurately reflecting the urban system due to inherent limitations of the data, models, and algorithms used (Ford and Wolf, 2020). When using ABM to represent human behaviour in a UDT, besides the risk of modelling it incorrectly, we must also question the ethics of relying excessively on such models, as in cases such as predictive policing (Karppi, 2018).

In discussions around data privacy and ethics, three main concerns surface: epistemic, normative, and moral responsibility (Tsamados et al., 2022). Epistemic concerns relate to fundamental questions regarding the nature of the data, its collection and utilisation, and access rights to it (Desai et al., 2022). In the context of when an ABM is used to represent human behaviour in a UDT, citizens might lack awareness of the comprehensive extent to which their data is collected, analysed, and shared, leading to a lack of clarity regarding the depth of the collected data.

Additionally, citizens usually express concerns about how public administrations use their data, mainly about the intended purpose of the use and the potential of data being shared with third parties (Trein and Varone, 2023). Cybersecurity emerges as a crucial aspect of this discourse, and in the context of UDTs cyber-attacks pose significant risks (Ferré-Bigorra et al., 2022). A breach in these systems could lead to the exposure of sensitive personal information and also potentially enable attackers to control essential urban infrastructures (Ferré-Bigorra et al., 2022; Lee et al., 2019).

Epistemic concerns highlight the importance of transparency and informed consent in data practices and also emphasise the need for individuals to have both knowledge and agency in making informed decisions about the collection and usage of their data.

Normative concerns might arise when ABMs integrated in a UDT leads to discrimination, inequality, or harm to population sub-groups, or to society overall. One of these concerns is the quality of data (Swarup and Mortveit, 2020). This directly impacts UDT simulations: when data is inaccurate and/or biased, it might hinder proper decision-making and future scenario projections (Nochta et al., 2021). For instance, data coming from citizens such as participatory sensing and crowdsourced data often suffer from human errors and lack of sensor calibration (Ferré-Bigorra et al., 2022; Kim et al., 2019; Sanderson et al., 2024). Moreover, unequal distribution of sensor measurement locations usually favours densely populated areas such as city centres, and also locations with more engaged citizens produce biased data which as a result raises fairness issues and marginalisation of certain groups (Robinson et al., 2022; Sanderson et al., 2024). Because simulation models and algorithms used in UDTs may reflect biases present in the data they are utilising, this might result in unfair outcomes or worsening existing inequalities in urban planning domains such as housing, transportation, or healthcare. Furthermore, the 'black box' approach to UDT design (lack of information on the used data, algorithms, and models) can lead to a lack of liability and understanding of how decisions are made (Barn, 2022). Addressing normative concerns requires careful consideration of principles such as attention to data quality, adopting open-source approaches, providing clear documentation of algorithms and data sources, and a balanced representation of all stakeholders' interests in the creation and management of UDTs.

Concerns regarding moral responsibility are related to the duties and liability of various involved stakeholders and entities engaged in the creation and management of UDTs. This arises from the fact that UDTs do not belong solely to a single entity or stakeholder but rather involve a collaborative effort among multiple parties (Batty, 2018; De Matos et al., 2022; Raes et al., 2021b). Although involved stakeholders and entities share the moral responsibility, identifying the precise responsibility and accountability mechanisms of each party within such a complex ecosystem is challenging. There is also the question of who will be accountable when the UDT makes a wrong interpretation and leads to bad decision-making that is detrimental to society and the environment (Ferré-Bigorra et al., 2022; Tzachor et al., 2022). Regulatory frameworks and governance structures might be needed to hold individuals and organisations accountable for their actions and can help enforce transparency and accountability standards.

Considering epistemic, normative, and moral concerns, including accountability, the question persists: How do we proceed ethically with a UDT when it can predict the behaviour of individuals explicitly linked actual citizens? In sensitive cases such as simulating a crime (Bosse and Gerritsen, 2008), for example, we may turn to a logic of preemptive policing (Egbert and Krasmann, 2019), targeting individuals solely based on the probability of committing a crime. Dedicated labs, such as the Ethical, Legal, and Societal Aspects (ELSA) AI labs,[1] that have been started in the Netherlands (Nederlandse AI Coalitie, 2020) may be helpful in this realm. However, the centres are at the starting point, and in part separated from technical innovation labs. It would be beneficial if ELSA concepts were integrated in the development of technology.

Finally, it is important to point out that all the discussion about UDTs and the incorporation of ABMs is based on the assumption that data are available to populate the UDT. However, the reality is that data availability and quality vary greatly between and within different regions of the world. This disparity underscores the need for a concerted effort to bridge the data divide (McCarthy, 2022), particularly between well-resourced areas such as the Netherlands and the less data-affluent regions, notably in the Global South. UDTs rely on a vast array of data, encompassing everything from geospatial and remotely sensed data, real-time sensor data for traffic patterns and energy consumption to environmental metrics such as air and water quality (Kitchin et al., 2015). In countries like the Netherlands, where the data infrastructure is robust, UDTs can achieve high levels of geospatial data coverage and accuracy, though even there numerous data integration and management challenges exist (Zheng et al., 2014). In other European Union countries, the data landscape is more fragmented and inconsistent. This variability undermines the potential of UDTs by limiting the scope of analyses and the applicability of insights derived from the ABMs. The challenges are even more pronounced in the Global South, where data scarcity and quality issues are compounded by infrastructural and technological limitations (McCarthy, 2022). These regions often struggle with the basic prerequisites for DT technologies, such as reliable internet access and digital literacy among the workforce. Bridging this data divide requires a multifaceted approach, focussing on technological infrastructure and capacity building. For countries lagging in data infrastructure, international collaboration and investment in data collection and analytics capabilities are crucial. Initiatives like open data platforms, public–private partnerships and possibly capacity building for digital literacy can play a pivotal role in enhancing data availability.

Future agenda

Here, we distil future agenda points that have arisen from our discussion about how ABMs and UDTs may add value to each other, but also which challenges will be faced in achieving such integration.

1. **The vision of a single, highly-detailed mirror of the city should be abandoned.** In the quest to build a digital city usable for everything, there is a high risk of producing something not useful for anything (Saltelli et al., 2024). The UDT's technical infrastructure to bring together different data sources (and potentially models) and visualize them is a positive development. But the purpose and corresponding vision and technology, and preferably also the used term (i.e. NOT twin), of UDTs should acknowledge that there is no single, complete view of the city. Data are incomplete and uncertain, theories are divergent and dependent on scale and purpose. Accounting for this is technically feasible, as demonstrated by the modelling community, but requires thought, redefinition, and studies on usability for the decision-making audience[2].
2. **UDTs should be made more suitable for sectoral (strategic) planning,** thereby ideally be capable of replicating the multitude of different social, environmental, and economic impacts of proposed changes in the built environment, thus moving beyond the Experimental Twin phase.
3. In this realm, **humans and other socio-technical entities should be represented in UDTs, for which ABMs could be a way forward.** We suggest to experiment with UDTs that include ABMs, as these provide a coherent way to capture behavioural and social processes. Two ways of integration we suggest, are the UDT as a live data repository and the UDT as live feedback between the ABM and the city. Benefits can only made tangible when the integration of UDT and ABM takes shape. Also only then, challenges may be faced that we did not foresee and may downplay the benefits discussed here.
4. **(Agent-based) modellers should foster a 'culture of cumulative research',** serving interoperability as well as theory development. Hereto, they should establish *structured guided*

frameworks (Groeneveld et al., 2017) to better inform and justify their decisions on how to model human behaviour, by critically engaging with dominant and alternative theories in the social sciences. This helps the creation of more robust models built on (theorized) cause-effect relations reflect the complexities of urban life rather than correlations derived from data. At the same time, they should promote and resort to (behavioural) *Reusable Building Blocks* (RBB), namely, blocks that regulate 'a particular mechanism or process that is relevant across many ABMs in a certain application domain' (Berger et al., 2024: p. 2). Without this, it is unlikely that ABMs and UDTs can ever be meaningfully integrated.

5. **(Agent-based) modellers should provide clarity about the purposes of their models.** This clarity is crucial as purpose determines fit-for-purpose of, for example, an ABM already developed in another study, and thereby validity and acceptance in the community of practice (Oreskes, 2019). A possible future direction may be to develop a grammar, which is a formalisation the different kinds of purposes of spatio-temporal model applications in an information pragmatic sense (Scheider and Verstegen, 2024). Such grammar could automate the selection of a fitting model within a UDT based on the research question posed in the study, with the added benefit of making this selection process transparent.
6. **Each UDT should make clear who holds the epistemic, normative, and moral responsibility for what,** before including data on individuals in the UDT instead of as an afterthought. This, in addition to our first point, should reduce the risk that UDTs 'end up being used as a political instrument for justification and control, eroding the basic principles of democracy' (Saltelli et al., 2024).

The question posed in this study's title was: Do UDTs need agents? In summary, our answer is: UDTs are in need of a more diverse perspective on the world, including their (currently lacking) perspective on the role of humans and other socio-technical entities in shaping the city. Though including agents may at some point be a solution for this lack, UDTs needs to be thoroughly revised first, in terms of (planning) purpose, vision, technology, and responsibilities.

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Data availability statement

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

Notes

1. https://nlaic.com/en/bouwsteen/human-centric-ai/elsa-concept/.
2. Though we suggest here to abandon the term UDT, we continue to use this term in the rest of this section for the sake of clarity and in absence of a new community-agreed term.

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Appendix A

Table 1. Interview questions with selected parts of answers from one of the interviewees.

Interview question	Selected quote related to answer
Please describe what your UDT looks like	Open urban platform. A centre piece in the digital infrastructure to connect everybody in an equal digital system, where they can exchange data, applications, services. The open urban platform is the infrastructure and we give meaning/ direction to it by putting the data concept of the digital twin on top of it.
Does it do simulation? What is the maturity level?	The municipality, as a government body, will put the rules in this infrastructure. So, metaphorically, how fast the cars can drive on this infrastructure, where the traffic lights are. Done that, different applications will be connected to that infrastructure.
What is your goal with the UDT? What problems do you want to tackle with it?	Bringing all different views connected to one single/basic layer. From the police making point of view, it is very important that we start by creating a common reality. Are we looking at the same reality? Yes. Only then create policies.
Have you already reached this goal?	The platform was recently released, though not all goals have been reached yet.
What are the challenges?	To create an equal system where tools can to talk to each other.
Where do you collect data from?	Openly available data.
What is missing from these DTs so that you can reach your goal?	We want to create rules for the digital infrastructure, and in the end a to a digital public space.
Do you see opportunities to include humans in it? Is there a lack of humans?	The digital twin is in the digital-physical dimension. People are left out because we believe people are an digital urban community, but not a digital twin. The digital twin is the first step towards a digital urban community.