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Moving from monitoring to real-time interventions for air quality: are low-cost sensor networks ready to support urban digital twins?

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Modern cities now have an increasing multitude of Internet-of-Things data streams on urban phenomena, including transport, mobility, and meteorology. One area of development has been the use of low-cost sensors to complement (or in some cases, substitute for) regulatory monitoring of ambient air pollution. As part of a bigger integrated approach to monitoring cities, such as Urban Observatories, disparate live data streams can now readily be collated and disseminated via a platform to facilitate the use of hyperlocal data for real-time decision making whilst supporting longer term sustainable development goals. Urban digital twins are the next logical step on this journey and these are becoming increasingly popular as a tool, at least conceptually, to better interpret this data as well as better understand the consequences of management interventions. To date, there are few examples of true digital twins of environmental challenges with many limited to the 'digital shadow' stage of development, characterized by lack of bi-directional feedback between the digital model and physical world. Urban Observatories present an opportunity to change this by providing the often overlooked, but crucial, underpinning foundations of urban digital twins. This paper focuses on the utilization of live stream data and demonstrates that air quality applications can provide a realistic target given the density of observations available, which can routinely be combined with other urban datasets to provide the added value and insights needed for urban air pollution management. However, the availability and standardization of live streams of big data is a major challenge and there are issues with interoperability, metadata management, communicating uncertainty, network longevity, data ownership and transparency. This paper contributes insights concerning how to overcome these challenges and calls for common practice in generating and managing live streams of big data.

KEYWORDS

air pollution, digital twin, low cost sensor, sensor networks, internet of things, urban digital twins (UDTs)

1 Introduction

Studies have demonstrated how the Internet of Things (IoT) can potentially transform the way in which air quality measurements (both indoor and outdoor) are made (Cowell et al., 2023a; Cowell et al., 2022; Ali et al., 2021; Hegde et al., 2020; Candia et al., 2018). Given the high spatial variability of pollutants in the atmosphere, the long-term reliance on a small number of 'high quality' sites has held back both our understanding of pollutant sources and dispersion, but also how the problem can be most effectively mitigated. Here, IoT not only facilitates the densification of observations to overcome this, but also the convergence of information, between devices themselves as well as with other sensors and further infrastructure (Vermesan, 2013). This enables the derivation of insights between a broader set of environmental variables, and their combined impacts, then previously possible.

Whilst this autonomous fusion of data is one application, this is only the start. The convergence of IoT technology goes beyond monitoring. With increasing devices moving online such as key infrastructure, mobile phones, vehicles and more, bidirectional communication between sensors and other device types, combined with increasingly ubiquitous artificial intelligence (AI) techniques, there is enormous potential for the approach to underpin autonomous real-time decision making and asset management (Bacquet and Vermesan, 2022; Mosco, 2017). Yet, to achieve this we need to go beyond deploying sensors and monitoring and resolve the challenges of data integration. This paper assesses the potential applications of this in the context of low-cost air quality sensors and digital twins. It aims to outline the next steps for this technology in supporting real-time decision making for cleaner air.

1.1 The Smart City

Smart cities integrate data and digital technology to increase sustainability, development, and quality of life in urban environments, often via the deployment of IoT enabled infrastructure and sensors that feed data onto online platforms (Mishra and Chakraborty, 2020; Ivanov et al., 2020). Smart cities cover a range of components: integrating smart infrastructure, health, homes, services, energy, industry, transportation, and agriculture to create sustainable societal benefits for citizens (Syed et al., 2021). The boom in low-cost sensors, specifically environmental monitors, means that cities are being monitored at a much higher resolution than ever before. These sensor networks allow for monitoring of environmental phenomena such as the urban heat island, public health (e.g., air pollution episodes) as well as the performance of infrastructure (Schrotter and Hürzeler, 2020; Ullo and Sinha, 2020; Chapman et al., 2015). The architecture of a smart city system embeds such sensors into a chain of communications and applications (Table 1). The IoT removes the limitations of traditionally required human data-input to computer systems and empowers the computer to "hear and sense the world" - assessing user needs and environment and communicating it to the relevant bodies (Ashton, 2009). These devices are increasingly vital to modern technical infrastructure as IoT systems can process the state of a 'thing' and feedback to users, creating unprecedented management and decision-making opportunities (Chapman et al., 2016; Zhu et al., 2010). It is now easy to know when a 'thing' need replacing, repairing, or adjusting without assessing the device in person. Whilst traditional statistical sampling can provide insight to this data, samples can be outdated by the time results are ready and can lead to delays in decision making until after an event occurs (Ivanov et al., 2020).

Smart cities have many potential advantages. They are designed with innovation and sustainability in mind, which means they often aim to integrate technology with environmental and social challenges associated with urban growth (Law and Lynch, 2019). They enhance the quality of life for citizens, by supporting the meeting of climate, energy and transport targets often aiming to reduce carbon footprint of city systems (Syed et al., 2021). They also create large economic incentives- both from the development of the technology itself and its contribution to society where the smart city can both generate new industries and innovation opportunities and save money by streamlining city wide processes. It is estimated that by 2025 the smart city market value will be between US$1–3.5 trillion (Syed et al., 2021; Law and Lynch, 2019; Mehmood et al., 2017).

However, despite the benefits of smart cities, there are challenges associated with their development. Defining a smart city itself is difficult. Many cities and projects use different criteria to describe themselves such as e-governance schemes, sustainability schemes and embedded communication technology (Syed et al., 2021). An example of this is the Living Labs movement, which whilst originally established in 2006 as programmes of innovative ecosystems based in real-life environments, have in practice had varied definitions and use cases (Schuurman et al., 2015; Følstad, 2008). Whilst many smart city elements exist and are documented within the literature, examples of wholly integrated infrastructure are rare. Most deployments focus on

TABLE 1 IoT architecture, information drawn from Syed et al. (2021) and Silva et al. (2018).

Layer	Elements	Description
Sensing layer	Sensors, actuators, mobile elements (aka car sensors, mobile phones data)	Generates information about physical phenomena via sensors. Actuators can act upon physical phenomena to generate/change data.
Network layer	Network technology and topologies	The layer that communicates data between hardware and software using wireless technology like Wi-Fi, Sigfox, Bluetooth.
Middleware layer	APIs, Databases, Security	The interface between data and application, including database management and security services
Applications layer	Services provided by using data	This layer provides end users with services by using forms of data analysis to inform and change the smart city
Business layer	Optimization, AI, deep learning	Attached to the applications layer, this uses complex data analysis to optimize performance and support the development of strategy and policies which manage the smart city system

single applications (e.g., air quality) and do not reach full integration potential by converging with wider applications. Smart city initiatives have sometimes struggled to address the needs of communities, being focused on technological deployments rather than societal needs (Martin et al., 2018). Furthermore, many applications do not even move beyond the demonstration stage with projects being decommissioned due to the closure of funding periods (Chapman et al., 2023a,b). For those that do, there still exists many interoperability challenges as various scales- from devices to network and applications. Technology in a smart city can vary in protocols and standards (or lack of) at these different levels represent barriers to integration success (Mehmood et al., 2017). Linked to this is the lack of open standards for operation and robustness when moving away from centralized deployments and integrating data from different sources (Syed et al., 2021). Security poses an additional challenge with 70% of IoT devices at risk of cyber-attack due to poor security protocols which leaves key infrastructure vulnerable (Mehmood et al., 2017). Finally, management of data presents security challenges in terms of anonymizing data that may be linked to people such as traffic and CCTV footage.

1.2 Urban observatories

The Urban Observatory (UO) approach was conceptualized to overcome some of the shortfalls of smart city projects. The fundamental ethos is that more can be learned by combining data from various sources, providing insights far beyond the means of which the data was originally intended. UO's act as a virtual platform bringing together urban data from an array of sources to enable a holistic view to the urban environment.

UO's collect data from the urban environment and engage stakeholders and potential users to facilitate data sharing and data-driven research and policy making. The first clear example of a defined UO concept was in the 1960s, when the term was used to describe a model in which science-based decision making and data collection was encouraged by partnerships between universities and governments (Dickey et al., 2021). This concept continued to evolve through the 4th industrial revolution and in the UK several UO's now exist, deploying and hosting an array of sensing and monitoring technology and working with various governmental and policy making agencies. Whilst some UO's directly refer to themselves as such, there are other institutions generating UO functions without the explicit title (Dickey et al., 2021). The UN-Habitat programme has guidance for UO's and sets out five generic aims that all observatories should try to cover, outlined below (UN Habitat, 2022);

1. *"Develop, collect and analyse data on a set of localized indicators to monitor a range of local or national priority issues—e.g. social development, economic performance, service delivery, etc."*
2. *"Establish long-term mechanisms for monitoring SDGs (sustainable development goals) and Urban indicators."*
3. *"Promote the use of urban data in planning and policymaking at local and national level."*
4. *"Disseminate information to strengthen accountability and transparency."*
5. *"Promote local ownership of urban indicators systems and a culture of monitoring and assessment."*

Whilst formally recognized Urban Observatories have a tendency to be research institution led, they can host an array of data live streams from external parties. An important consideration of the UO approach, is that in addition to deployed sensors themselves, they also host a range of 3rd party data that is applicable to urban management. Examples include ANPR devices and air quality sensors that are operated and managed by public and private bodies but that share their data with their local UO. The UO platforms create a space for live stream contributors to publicly share data without having to invest in new online infrastructure and synthesizes the somewhat ad-hoc nature of accessing live data streams. Bringing the data together in a single place has the potential to drive entirely new innovation ecosystems.

Overall, the UO approach unlocks the potential for the application of the vast streams of real-time data collated by the observatories to be used beyond what has been possible with traditional monitoring efforts. The 'live' nature of the data and common platform improve the temporal rate at which decisions can be made from data. Combined with increasing technological advances such as modelling systems and AI, this has led to interest in simulation and decision making from this data as part of a bigger digital twin agenda. UO's are well placed to support the development of digital twins as the aims of long-term data, transparency, relevance to urban challenges and promoting urban planning align with the needs and aims of urban digital twins.

1.3 The growth of air quality data sources

Air quality sensors are a key common component of both UO's and smart cities. The growth of the low-cost sensor market means that sensor networks are being deployed at unprecedented spatial scales (Karagulian et al., 2019; Snyder et al., 2013), with sensors for air quality now featuring high on the priority list for smart cities across the globe. Low-cost sensors for air quality range in price from <£100 per unit for a basic sensor component with no additional communications or data storage, to £1000's per unit for multi-pollutant sensors with built-in communications, data management and corrections and online data storage. Although low-cost sensors allow for a cost effective solution for a more ubiquitous air-quality monitoring, they come with technical limitations in their sensing capacity that make them less reliable than more expensive devices (Kang et al., 2022; Cowell et al., 2022; Karagulian et al., 2019).

As an example, some the types of sensors and data streams being generated by Urban Observatories are outlined in Table 2. This is a non-exhaustive list and includes commercially manufactured low-cost monitors, DIY or sensors designed "In-house" by researchers and government regulatory sites whose open data was integrated where possible. Note that the list is non exhaustive list of examples, and there remain unknowns within the featured examples. This is due to the ad-hoc nature of live stream hosting and reporting, making it challenging to identify which cities have live AQ streams, how they can be accessed and which technology they used (even when exploring repositories of UOs such as the one from UN-Habitat) (UN-Habitat, n.d.). Whilst Table 2 features some examples of UOs, there are also cities that have AQ monitoring that are not part of wider smart city, or UO programmes. This is where the potential of UOs to support digital twins becomes prominent, offering an opportunity to collate existing data streams to create holistic insights into urban challenges.

TABLE 2 Examples of air quality data streams in cities. (non-exhaustive list).

AQ monitors used (if known)	Location	Commercial sensor, regulatory monitoring or in-house design sensor (if known)	Pollutants measured
QuantAQ, Emote, DEFRA AURN, AQ Mesh, Zephyr, AltasensePM, Purple Air	UK Urban Observatories (Birmingham UO, UK Newcastle UO, UK Manchester UO, UK Cranfield UO, UK)	Commercial, Regulatory and In-house design	CO, CO_2, NO, NO_2, O_3, PM_1, PM_{10}, $PM_{2.5}$, SO_2
PurpleAir	Lahore, Pakistan	Commercial	PM
LEO	CITI-SENSE EU observatories (including Belgrade, Serbia)	Commercial	NO, NO_2, O_3
Unknown devices	Bangkok, Thailand	Unknown	CO, NO_2, O_3, PM_1, PM_{10}, $PM_{2.5}$, SO_2
Airly	Warsaw, Poland	Commercial	PM_1, PM_{10}, $PM_{2.5}$
Ai_R	Johannesburg, South Africa	In-house design	PM_1, PM_{10}, $PM_{2.5}$, PM_4
Breathe London Nodes provided by Clarity	London, UK	Commercial	$PM_{2.5}$, NO_2
Clarity node-s	Paris, France	Commercial	$PM_{2.5}$, NO_2
Clarity node-s, purple air, regulatory	South Coast Air Quality Management District, California, USA	Commercial, regulatory	PM_{10}, $PM_{2.5}$, NO_2, CO, O_3

Sources: Living Laboratory (n.d.), Jovašević-Stojanović et al. (2016), Air4thai (2024), City of Warsaw (2022), Mellado (2024), SACAQM (2021), Environmental Research Group (n.d.), Clarity IO (2018), South Coast AQMD (n.d.).

In the UK, the government regulatory stations (DEFRA AURN) are reflective of traditional monitoring efforts- however commercial and low-cost sensors are growing in popularity with local authorities to compliment regulatory methods by providing air quality data at greater spatial resolutions (Morawska et al., 2018). An example of this is the Zephyr data array from Birmingham, which consists of a mixture of university and third party owned units. Another example of widescale low-cost sensor deployment is the PurpleAir network of PM monitors, which is the largest network of monitors in the USA (over 20,000 units deployed since 2017) and includes units deployed by individuals, community groups and local authorities (Wallace et al., 2022).

1.4 Digital twins

The term digital twin is defined as '*a virtual representation of the characteristics and behaviors of a physical object*' (Papyshev and Yarime, 2021). Core to the concept of a digital twin is the connection between the physical and the virtual products. In digital twins the virtual model and the physical model do not stand alone and are integrated (Papyshev and Yarime, 2021; Jones et al., 2020; Tao et al., 2019). Initially developed in manufacturing, digital twins create an ever-evolving model of the real world which is fed by the growing wealth of data from the IoT boom which can support monitoring and understanding of the physical world to improve human wellbeing (Fuller et al., 2020; Saddik, 2018).

Precursors to digital twins were digital models and shadows. A model is usually a term used to describe a simplified mirror image of a process, often focusing on features that are under scrutiny by the user and discarding other features considered not relevant to a project (Batty, 2018). Digital shadows are models which represent a physical phenomenon and have one way communication, with the physical entity feeding into the digital model only, creating a so-called shadow of the real world (Sepasgozar, 2021). Importantly, the digital shadow does not feedback into the physical. This means that any insight derived from analysing the shadow model is not actuated in an automatic fashion in the real word but needs the mediation of humans. There are no actuators that are triggered automatically to change the real world by the results of the model analysis.

One of the current issues in this research area is that the terms digital model and digital shadow are frequently, and incorrectly, referred to collectively as digital twins. A true digital twin is not static. Whereas models are built off baseline data to create estimates of scenarios, digital twins experience automatic data exchange between the digital image and inputs from the physical object being mirrored (Fuller et al., 2020; Batty, 2018). Fundamentally, this communication with the real or 'physical' twin occurs in real, or near real time, is two-way and is often facilitated via IoT enabled sensors detecting important phenomena within the physical twin. AI (such as machine learning) is then often utilized by the digital twin to make decisions based on the information from the physical twin (Saddik, 2018). Through this bidirectional feedback, digital twins allow for online testing of decisions and detection of failures ahead of occurrence in the physical world, saving costs, time and resources (Sharma et al., 2022).

This approach provides novel opportunities for decision making- by utilizing real time IoT data to manage key infrastructure within the city. For example- the impact of extreme weather events can be detected via sensors, fed into the digital twin alongside city scale infrastructure data to assess the impact on transport infrastructure, allowing interventions to be tested for efficacy ahead of time and then translated into the real world to limit disruption (Schrotter and Hürzeler, 2020). The data from the physical twin during the management is then fed back into the digital twin to help the AI learn and improve. Examples are available from a range of sectors, underlining the wide array of applications of digital twins. NASA use digital twins to monitor spacecraft during flight, Chevron use digital twins to monitor wind turbine operations and are even being used in cardio-vascular medicine to help test recovery pathways of patient treatment (Corral-Acero et al., 2020; Tao and Qi, 2019). The increasing use of IoT technology and rapid computational developments mean that the possible applications of digital twin technology are vast.

However, while digital twins are now common in other sectors, environmental examples at scale in the real world has been limited. A rare example is the Climate Resilience Demonstrator (CReDo) digital twin (shadow) project aimed at improving resilience of energy, water and communication networks from climate change driven flood and weather risk. The initial phase of CreDo integrated data from a major water supplier, power company, communications company and the Met Office onto a digital twin, allowing users to view embedded failure changes that could occur in changing climatic events such as heavy rains and droughts (Digital Twin Hub, 2023). The digital shadow nature of such projects underlines the challenges in producing digital twins for environmental applications. Although there is a movement to overcome this, at least in nomenclature, by discussing 'environment aware' digital twins (e.g., Dale et al., 2023), in many cases, this is a result of jumping straight to the familiar territory of modelling and simulation rather than ensuring the fundamentals of real-time data curation, i.e., metadata and interoperability, are adequately addressed.

Urban digital twins are also limited in their development. A recent review identified only 22 urban digital twins discussed within high quality peer reviewed literature, with the majority of these being based in Europe and only one in the global south (Morocco) (Ferré-Bigorra et al., 2022). Of these studies, the vast majority of digital twins were either prototypes or under development, further underlining the novelty of digital twins for urban decision-making. Of the four studies recognized as reflecting operational digital twins, real time monitoring was a concurrent theme, exploring the disagreement between models and sensors, and the increasing number of sensors at lower cost, and using data from sensors deployed by both researchers and non-academics alike (Pedersen et al., 2021; White et al., 2021; Sofia et al., 2020; Dembski et al., 2020). It is unsurprising that digital twin technologies have such a focus on the global north when we know that data inequities exist, and data is at the core of digital twin technologies. For example, for air pollution, in Europe, the US and Canada 69.2% of governments produce open data whereas in Africa only 6.8% of governments produce open data (Hasenkopf et al., 2023).

Moreover, despite the growth of air pollution data from sensor networks and projects such as Urban Observatories and Smart Cities, there are limited applications of using these live streams in digital twin contexts. Hristov et al. (2022) demonstrate a use case for an urban living laboratory to validate, calibrate and enhance predicative capability of computational simulations but do not suggest real time or dynamic air quality management from live stream data. Lopez de Ipiña et al. (2024) evaluate the suitability of low-cost PM sensors for digital twins in a manufacturing context but report that without proper management, uncertainty and biases limit application. The review mentioned above identified only 5 (of a total of only 22) existing urban digital twins modelled atmospheric pollution and 3 collected atmospheric pollution data using sensors with digital twins being very much focused on their specific use cases for their data sources (Ferré-Bigorra et al., 2022). This paper calls for a focus on the challenges and opportunities of digital twins and low cost sensors, before presenting potential use cases of digital twins for dynamic air quality management using low-cost sensor networks data.

2 Challenges of achieving large scale digital twins

2.1 National Digital Twin Programme

The UK has an ambitious vision to integrate a national digital twin and in 2018, the National Digital Twin Programme (NDTP) was launched to support this aim. The NDTP focusses on generating a collection of interconnected digital twins rather than one individual large twin. These twins will be developed by a range of organizations but will be interoperable, using federated and standardized systems to support decision making across a range of fields (Government Office for Science, 2023). The programme is a collaborative effort between industry, government and researchers (Digital Twin Hub, 2022). This is an ongoing effort, however, there have been some key outputs from the programme already that will shape the formation of the digital twin to ensure that the NDTP meets its promise of delivering benefits to society, economy, business and environment (Centre for Digital Built Britain, 2022).

There are significant challenges facing the NDTP; fundamentally around the utilisation of large datasets. When integrating data from multiple sources, the metadata becomes as important as the data itself. It is important to consider factors such as who owns the data at each stage, how the data is protected, what computational power is required to process and store such data and are datasets interoperable. Away from technical questions, there are also ethical challenges around big data usage, ensuring that data does not further inequality and is not bias towards certain populations is one challenge. Another comes in the form of the collection and security of sensitive data that is integral to multi-sector digital twins (Government Office for Science, 2023). One key advance in this space is the Gemini Principles which set out the key principles needed to build a national digital twin that meets the above promises and considers the challenges highlighted (Centre for Digital Built Britain, 2022). Outlined in Figure 1 below, the Gemini Principles are a tool to ensure that a digital twin framework is purposeful, trustworthy and functional to enable better operability, management and delivery of digital twin assets (Bolton et al., 2018). However, it is not possible to fully apply the Gemini Principles to air quality data sets- sensor networks face challenges around governance, regulation, ownership. The data sets are not yet long term, both due to the life span of sensors frequently being suggested as 1–2 years by manufacturers and the 'project limited' mindset in which environmental data is often procured. A further limitation to progress towards the Gemini Principles is the data skills shortage currently experienced in the UK. In 2021, the Department for Education stated that 52% of the workforce for not have the essential digital skills required of modern work (Department for Education, 2021). Without these skills, it is unlikely that data will be suitable to progress towards a digital twin, nor will the workforce be able to develop and integrate digital twin technology readily into decision making processes. Given the scale of the research required, a national digital twin remains a long-term ambition. Progress will comprise of building blocks of much smaller digital twins—perhaps for a particular sector, location or use-case, which can later be integrated as bigger connected twin.

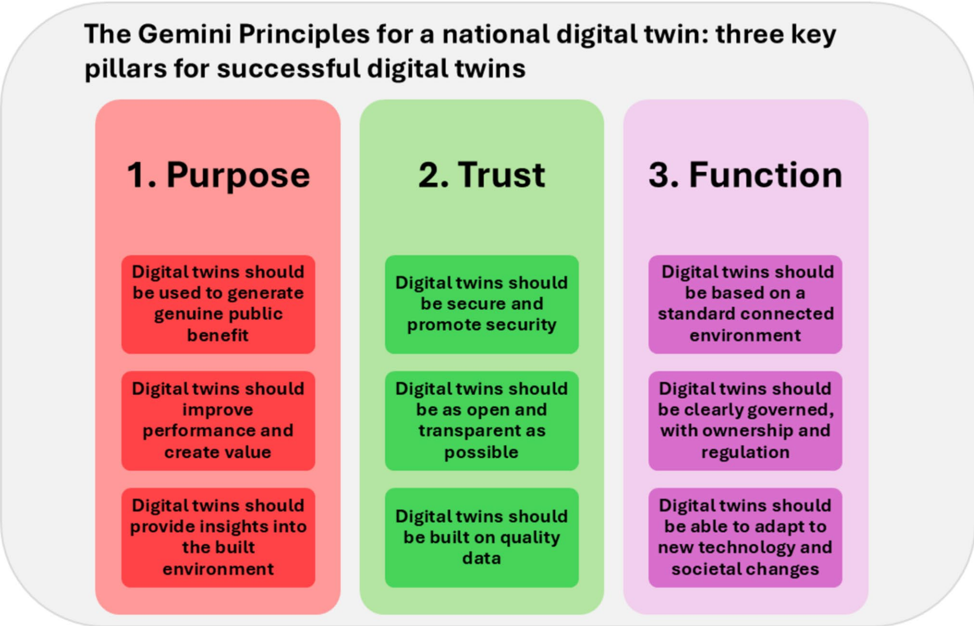

FIGURE 1
An overview of the Gemini Principles adapted from Bolton et al. (2018) under CC BY 3.0 licence.

There is a clear need for collaborative effort of harnessing data for digital twin use in the UK, particularly real-time data that could support autonomous decision making. It is this data which will fundamentally underpin any digital twin in this space, regardless of size. An example of such data could be the real-time data from a low-cost air quality sensor. Combining data from low-cost sensor networks alongside regulatory and commercial instruments has already been demonstrated in Cowell et al. (2023b) to expand spatial understanding of air quality, and thus this is a clear candidate of data that could be utilized to create more sustainable decision making. There is also opportunity to expand the coagulation of data further, via the UO concept, onboarding other relevant datasets such as traffic data to enhance decision making efforts further. The problem is this area of research is less eye-catching than that involved for modelling and simulation. However, without the fundamental principles (such as those proposed by the Gemini Principles) being firmly established in this area, a large-scale digital twin is simply not possible.

2.2 Interoperability and metadata of live streams

An important first step in bringing together the wealth of air quality data from low-cost sensors alongside regulatory measurements and wider air quality related indicators (such as traffic data and meteorology) is a standardization of data protocols. Data catalogues can be used to collate and store metadata around live streams and if managed correctly can provide insight into the health and applications of a data stream. While metadata is often collected by individual projects deploying low-cost sensors, there is not one clear method of data standardization to make collating data easier. Metadata is vital for enabling the use of smart city data, enabling decision makers to understand the data being provided by the IoT networks (Schrotter and Hürzeler, 2020). It is an imperative feature of data streams that will be used for digital twins, as it describes characteristics of the digital twin it will form, such as data refresh rate, digital twin spatial coverage and data quality and uncertainties. The best suited datasets for digital twin use will capture as much metadata as possible to support end users. Without metadata it is challenging to assess a stream's health and applicability to a use case. Furthermore, low-cost sensors present new challenges that need to be captured by metadata. They can experience mechanical and electrical issues due to exposure and damage from the natural environment, as well as power outages, lack of maintenance, drift, changing calibrations and data processing procedures (Chan et al., 2021; Shakeri et al., 2020). For example, PM samplers have been reported in the literature as being calibrated using both static and variable calibrations, being calibrated against different reference instruments, being calibrated using different statistical models to correct sensor values, different models performing differently and performing differently dependent on aerosol composition (Crilley et al., 2018; Cowell et al., 2022; Bulot et al., 2019; Crilley et al., 2020; Di Antonio et al., 2018; Sayahi et al., 2019; Tryner et al., 2020; Zusman et al., 2020; Zou et al., 2021). Therefore, to capture these nuances, metadata will require detail and regular updates to ensure these changes, and any other data outages or challenges are visible to the user.

One of the key challenges to generating metadata is ensuring terminology and understanding of terminology is uniform across datasets (Saddik, 2018). Without having agreed standards and a standards body, the use of livestream data for digital twins will be limited. The FAIR guiding principles for data are designed to increase the usability of data, both by individuals and machines (Wilkinson et al., 2016). They align greatly with the Gemini Principles for digital twins, both promoting the transparency, openness and quality of data to allow for verification and functionality of data. The FAIR principles have 4 components:

1. Findable: *Both humans and computers should be easily able to find both data and metadata. Datasets should include a identifier, rich metadata, metadata should clearly state the identifier of the data it describes and data should be registered in a searchable resource.*
2. Accessible: *It should be clear how users access data, including authentication and authorization processes. This entails data being retrievable via a standard communications protocol and that the protocol is free and open. Metadata should also continue to be accessible even when data is no longer available.*
3. Interoperable: *Ensuring data is able to be integrated with other data or applications by providing metadata in a formal, accessible and applicable way, using vocabularies that follow the FAIR principles themselves.*
4. Reusable: *If data is to be useable, data and metadata needs to be described well including providing rich metadata with clear and accessible data use licence rules. It should be clear where data and metadata originated from.*

(Wilkinson et al., 2016; Kinkade and Shepherd, 2022; Wang and Savard, 2023)

However, even with internationally recognized principles in place, practical methods are needed to meet them and they are not always fully met. As already discussed, live stream data from UN Habitat Urban Observatories proved to be anything but findable. Indeed, research suggests that the principles are somewhat aspirational and it is much harder to achieve the interoperable and reusable components of the FAIR principles than the findable and accessible components (Kinkade and Shepherd, 2022). Whilst FAIR is a set of principles that should inspire good practice, they are explicitly not described as data standards and are not a prescriptive method for managing data (Mons et al., 2017). They allow for varying approaches to data management and thus, for digital twins, there is still the challenge of data standards particularly with the increasingly heterogeneous nature of data sources from the IoT boom.

Ontologies provide a solution to ensure that the various components of metadata for live streams are standardized and universal, supporting the interoperability and reusability of data. Ontologies allow for streamlined management of complex data by organizing data semantically and intuitively and making it easier to integrate data into different interfaces (Erkoyuncu et al., 2020; Kharlamov et al., 2018). To further enhance and future proof the standardization of metadata efforts, data models are an excellent way of enabling compatible representation of entities for interoperable smart solutions whilst allowing for growth with changing technology. Open-source information models for data (aka Smart Data Models) offer great opportunity here. It is important to recognize that Smart Data Models are different to ontologies. While an ontology focuses on representing real-world entities in a way that replicates our understanding of the entities' properties and characteristics, a smart data model focuses only on agreeing on a set of descriptors that make sense for the people involved in specific domains, without too much regard for describing real-time entities as they appear in the real world. Smart Data Models are dynamic formats and semantics that can be used to share data in a standardized way, which are adaptable and informed by feedback from users to ensure they are fully capturing the wealth of information required by applications (Smart Data Models, 2023; Abellagarcia, 2022). For example, in the context of low-cost sensors models can be adapted to contextualize challenges such as those around ownership of sensors and data, and 3rd party sensor providers. This allows the models to evolve with technology-ensuring they continue to support data interoperability within rapidly developing fields (Smart Data Models, 2023).

Air quality sensors provide an ideal target domain to test these underlying principles. Firstly, the abundance of sensors from different manufacturers, measuring different parameters in different settings poses a vast, but manageable, challenge in itself (e.g., Table 2) (Topping et al., 2021). Air quality metadata is imperative to understanding the uncertainties associated with measurements, especially with low-cost sensors which are prone to environmental interference on performance and can have undisclosed calibration algorithms (Cowell et al., 2022; Cowell et al., 2024; Crilley et al., 2018). Digital twins will require the merging of real-time data streams and real-time metadata updates to support the filtering of data used for decision making based off of the health of a data stream. Moreover, the growing market of sensing as a service is making air quality monitoring more attractive to city stakeholders that do not have technical and data skills. This means there is increasing air quality data available in cities for decision makers that is open to automated decision making. The advantage of using air quality as a target is that there is also low-hanging fruit in terms of use cases where real-time, autonomous, decision making could make a significant improvement for public and environmental health in a relatively short time frame.

3 Air quality use cases

Air quality management and traffic management can have a symbiotic relationship. Often the best practice for traffic management that reduces congestion and smooths traffic flow also leads to positive impacts for air quality. Current examples of traffic management for targeted AQ benefit include static signage and 'do not drive' campaigns. For example, static signage, which warns people of the impact of their driving behavior, has been reported to reduce PM2.5 concentrations in Canterbury, UK, where road signs were displayed at a rail crossing encouraging drivers to turn off their engine whilst waiting resulted in behavior change and reduced concentrations (Abrams et al., 2021).

In Stuttgart, Germany, multimedia messaging via signs and local broadcasting encouraged 'Do not Drive Appeals' during forecasted periods of high PM concentrations (based off seasonal meteorologically driven decision tree). This city wide (i.e., blanket message) method caused minor reductions in city centre traffic during weekdays but also had potential to increase traffic on city periphery (Dangel and Goeschl, 2022). Further examples of traffic management for air pollution control generally are static, creating standardised inflexible changes to traffic management (Thomas, 2022; Thomas et al., 2022; Hopkinson et al., 2021; Dajnak et al., 2018; Gustafsson, 2022; Laverty et al., 2021; Schmitz et al., 2021; Pattinson et al., 2017). However, the IoT is starting to be enable and create potential for data driven decision making (for example via traffic camera derived real time vehicle counts). IoT enabled solutions are developing, making real-time and dynamic decision making a possibility (Carter and Rushton, 2020), which will ultimately underpin the emergence of digital twins in this area. Some examples of where digital twins could support dynamic decision making for air quality include.

3.1 Dynamic messaging

IoT data has already being integrated into traffic management via real time citizen information. Variable Messaging Signs (VMS) which provide guidance to road users are being used to provide updates when air quality crosses a threshold concentration, triggering signage to advise traffic to alter their routes to avoid identified hotspots (Chaplin and Taylor, 2020). Signs display real-time travel times by public transport and air quality information to encourage the public to utilize public and active travel over private vehicle (Coventry City Council, 2007; Barrett, 2019; Stieldorf et al., 2020). Currently, variable messaging is one directional, i.e., when the air quality concentrations exceed a threshold, the traffic messaging is updated. However, AI could readily be used to develop this further allowing for AQ predictions to be generated from the sensor data to allow for preventative decision making. Real-time data could also be used to generate predictions a short time into the future (hours-days), allowing the council to visualize potential hotspots and use traffic advisories to prevent them before the threshold concentrations are crossed. The digital twin approach could extend this integrating other data sources, traffic counts and vehicle speeds from cameras integrated into a UO platform to monitor and adapt to the reaction of traffic to VMS driven from AQ predictions and update route guidance and traffic flow via traffic lights accordingly for maximum efficiency and lowest environmental impact.

3.2 Traffic routing

A more ubiquitous example of real-time traffic management with air quality benefits is the use of modern navigation applications by drivers. The optimization of route mapping for travel time (based on real-time traffic data) can also lead to air quality improvements (Huang and Hu, 2018). Novel research is creating new opportunities for traffic routing for air pollution management. This includes the integration of telematics data from navigation applications to fleet composition and emission factors to infer real time pollutant emissions (Ghaffarpasand and Pope, 2023). Whilst so far, this technology focuses on exhaust emissions, there is scope to expand tools to consider increasingly important non-exhaust emissions [supporting particulate matter management during the decarbonisation and electrification of vehicle fleets (Cowell et al., 2023b)]. Ultimately, low-cost sensor data could feed back directly into traffic routing apps supporting the routing choices by combining telematics and real time pollution data into the routing algorithm to mitigate emissions from motor vehicles.

Digital twin technology and traffic routing can also adapt behavior to reduce exposure to pollution. Evidence suggests that the more cyclists are segregated from traffic, exposure to air pollutants decreases (Schmitz et al., 2021; Dajnak et al., 2018; Pattinson et al., 2017). Online tools already provide cyclists with routing options, using static map data to suggest various routes by level of busy-ness and speed to support cyclists varying confidence levels (Cyclestreets, 2023). The open-access principles at the heart of digital twins mean that air quality and traffic data could be available to enhance such tools to also factor potential exposure to pollution into mapping suggestions.

3.3 Controlling traffic flow

'Green Wave' is a method of traffic management in which the signal sequence is optimized to limit congestions by creating a flow where traffic can pass through junctions without meeting a red light (Xu et al., 2014; De Coensel et al., 2012). The goal of a Green Wave is to reduce congestion and by proxy, vehicle emissions by optimizing flow. It has been suggested Green Waves should target reducing non-essential stop-starts and idling in areas where people are at higher risk of pollution exposure (such as pedestrian crossings) (Xu et al., 2014; Kelly, 2012). Sensors could be utilized here alongside other traffic data to optimize the Green Wave process, highlighting particulate hotspots where traffic stop/starts should be limited. Smart traffic lights can already integrate infra-red detectors and wireless communication regarding congestion to streamline performance-pollution concentrations are an obvious next step in enhancing this further (Oliveira et al., 2021).

3.4 Testing interventions

There is opportunity to utilize digital twins for agent-based modelling of air quality interventions. The growth of live stream data can allow for more complex modelling of interventions, integrating data at higher resolutions, from a range of sources and including a greater range of variables (Topping et al., 2021).

A current example of this is low traffic neighborhoods, a controversial air quality intervention which are designed to promote health and wellbeing by reducing traffic and air pollution in residential areas (Whelan et al., 2024; Yang et al., 2022). Low-traffic neighborhoods are most popular in urban areas in the Global North, where generally access to air quality and traffic data is available. Research has already combined data from travel activity alongside model and measurement data of air pollutions to simulate exposures of populations to PM2.5 (Thomas et al., 2022). However, the growth of live stream data and increased air quality observations from low-cost sensors can enable the generation of digital twins of LTNs. This can be used to test an intervention ahead of time and adapt and optimize it in real time based on traffic and air quality observations and digital twin predictions. This could also help garner public support of successful, but controversial, interventions such as LTNS. This methodology could be applied to an array of interventions and could be used to evaluate and adapt interventions dynamically depending on live data from the city. Clean Air Zones, School Streets, Congestion Charges, Zones of interventions could be adjusted to reflect the real-time traffic patterns, meteorology and pollution concentrations after a digital twin has anticipated the potential best outcomes of various scenarios interpreted from live data.

3.5 Summary of air quality uses for digital twins

In summary, there are varied use cases where digital twins could enhance existing air quality interventions in cities. Transport related interventions are an obvious target for digital twin enhancements due to the availability of transport related data in many cities; either from hard infrastructure such as smart traffic lights, sensors and traffic cameras, or from online mobility software (navigation apps, GPS data). Digital twins bring an opportunity to optimize solutions for both emissions and exposure reduction, helping to manage the conditions to reduce vehicle emissions and helping to create cities which direct populations away from hotspots and areas of high emissions. Digital twins could make existing solutions more dynamic, shifting from static observations and reactive interventions into dynamic, predictive and adaptable solutions. The evidence generated by digital twins could also help optimize solutions, supporting public consultation processes and supporting informed and evidence-based decision making for future interventions.

4 Challenges of live sensor data

Whilst air quality monitoring is not novel practice, the development of more agile, connective, low-cost sensing is enabling a new paradigm of urban decision making. However, there are challenges in making this a reality. The first challenge is ensuring that the low-cost sensor networks are thoughtfully deployed and maintained. Whilst this research does not focus on the practicalities of air pollution sampling using low-cost sensors, it is important to ensure any low-cost sensor deployment is reflective of the latest research and considers:

- The needs of the end user and whether the sensors meet this (Cowell et al., 2023a,b,c).
- That sensors are robustly calibrated ideally in local conditions (Crilley et al., 2018; Cowell et al., 2022; Di Antonio et al., 2018; Zusman et al., 2020).
- The environmental influence on sensors (humidity, interference from local sources, power supply, temperature, aerosol composition) (Cowell et al., 2022; Crilley et al., 2020).
- The sensor is able to detect the pollutant of concern (which is particularly important with PM samplers which may not be able to detect all size fractions of aerosols) (Ouimette et al., 2022; Tryner et al., 2020; Molina Rueda et al., 2023).

Table 3 outlines the key challenges in embedding air quality sensor technology into digital twins. Firstly, embedding unstandardized low-cost sensor data into integrated UO platforms presents a significant, and arguably overlooked, challenge, but the infrastructure to support interoperability is now becoming established, with ontologies and data models developed specifically with the aim of ensuring interoperability and longevity of metadata methods. There is a clear need for agreed upon data standards and standards bodies to maintain data uniformly. An example of this in practice would be the W3C web standards; which were co-developed by users and consulted upon both publicly and with other standards bodies to ensure they met consensus, were accessible, reflected the needs of diverse stakeholders and are interoperable (The World Wide Web Consortium, 2024). These standards are dynamic, evolving with the needs of the stakeholders through participatory design (Abou-Zahra and Brewer, 2019). Digital twins and live stream data need a comparable champion, a body that can work to design and implement standards and interoperability (Abou-Zahra et al., 2017). The World Wide Web Consortium (who developed W3C) and the Open Geospatial Consortium contributed to the development of ontologies for sensor data, the SSN and SOSA modules however these are not yet uniformly adopted by sensor data mangers and urban data is still fragmented (Haller et al., 2019). There is potential for governance to play a key role here, to force a level of standardization into live data streams.

Secondly, low-cost sensors, particularly for air quality monitoring, often raise concern within the scientific community due to both their data quality and lack of a uniform method in solving calibration and data quality issues (Kang et al., 2022; Morawska et al., 2018; Rai et al., 2017). Whilst good practice in data processing, sensor deployment (Cowell et al., 2023b) and management can overcome the limitations associated with low-cost AQ sensors (impact of humidity, pollutant source, drift), there is not a uniform approach to this with researchers presenting different methods with varying degrees of success (Popoola et al., 2018; Rai et al., 2017). Whilst sensors such as AltasensePM, a sensor developed in-house at University of Birmingham, has peer-reviewed calibration and validation methods which are scalable.

Next, the 3rd party management of sensor networks also creates challenges. Many AQ sensor providers offer data management as part of their data collection service as they shift towards a subscription business model and seek to build up valuable data. Whilst the hardware of many commercial AQ sensors is often the same components, the software is the way sensor companies can market a unique product. Whilst some offer raw data direct from the sensors, other advertise packages that include data calibration and management where the company will use proprietary software to calibrate and correct the sensors to make data collection easier for the non-scientific target market. As these methods of correction and calibration are a unique selling point to the business, the methods are often kept private and only shared in very basic detail with the consumer meaning end users are unlikely to know exactly how data has been manipulated and if these manipulations fully address data quality issues outlined in the literature. Some sensor companies then present data at a cost by making it available via locked software only and charging for access. This limits the availability and usability of this data (see Table 3).

Furthermore, in countries where emissions from traffic sources are decreasing, the importance of near source monitoring at roadsides is being thrown into contention. Regional and transboundary PM sources from further afield is going to become increasingly important to monitor and understand and this will require wide scale monitoring at an international scale in a standardized way if this is going to be fully reflected into any future potential digital twins. Indoor air quality, bioaerosols and an ability to understand personal exposure will all become more important to managing the environment to improve human health. All display similar requirements around metadata and the accuracy of sensors to be useful for digital twinning.

Furthermore, as low-cost sensor networks are accessible to communities that are not directly from a scientific research background, there is no guarantee that data interpretation methods used will be appropriate for generating reliable data for decision making applications (Morawska et al., 2018). Even if sensors are undergoing proper data management, this may not be captured fully and shared which makes capturing and understanding data from external stakeholder networks challenging. This is particularly challenging in the UK as the government recognized digital skills shortage, meaning that many workers are ill prepared for managing and interpreting the technology needed to support sensor networks, let alone digital twins (Department for Education, 2021).

TABLE 3 The key challenges for low-cost air quality sensors and digital twins.

Interoperability	Calibration and data quality	Sensing as a service	Longevity	Data accessibility
Lack of standardized language for metadata, included varied ontologies and organizational structural used for describing live streams.	Low cost sensors require additional QA:QC and calibration due to their varying accuracy	Some sensor manufacturers that offer sensing as a service use proprietary software to calibrate sensors. This is often undisclosed.	(Research) project based mindset behind environmental monitoring can lead to short term monitoring efforts.	Digital skills shortages leads to data not being used or misinterpreted.
Missing metadata makes it challenging to integrate data streams.	There are varying methods for sensor calibration.	Raw and calibrated data can be hidden behind a paywall when using these services.	Project style funding means there is a lack of funding to host live streams in the long term.	Sensors uncertainty can be challenging to communicate.
Not all metadata or data processing is transparent.	Low cost sensors performance data quality is not comparable to regulatory grade instrumentation and is impacts by environmental factors.	Data and digital skills shortages encourage the uptake of sensing as a service.		

Beyond these challenges of sensors, there is debate around the feasibility of current air quality sensors supporting digital twins. Air quality sensors are still not uniformly or widely spread covering the entirety of nations so the opportunity for a national digital twin for air quality (such as proposed in the UK), or national use cases of digital twins is not yet likely. Moreover, the uncertainty associated with low-cost sensors means that for now they are best suited for indicative insights into air pollution rather than precise measurement to a specific concentration number (although technology and calibration methods are rapidly developing so this will likely change in the future). Due to the limited sensitively of low-cost sensors, digital twins use cases requiring specific particulate matter concentrations are currently limited however, regional decision making is feasible as sensor networks have shown that they can provide good insight into regional patterns and identifying high pollution events (Cowell et al., 2023b). Examples of this include resource management such as informing healthcare systems of potential risk for increased regional concentrations of pollutants and providing real time citizen advice around outdoor concentrations during regional peaks, such as reducing outdoor activity by real-time messaging. The best placed networks for supporting digital twins currently are those that integrate data types, such as reference data, model data and low-cost sensing data to give a holistic picture of air quality. Networks and platforms that integrate this data with other real-time data such as resource availability, traffic and activity and meteorology and likely to be best placed to be integrated into potential digital twin technology.

5 Conclusion

Overall, as shown by the example use cases in this viewpoint, there is clear potential of low-cost AQ networks to inform digital twins, but barriers remain which need to be tackled. Unfortunately, these barriers are rooted in the fundamental operational aspects of maintaining and standardizing live feeds of data that are crucial to real-time decision making. Unfortunately, this represents an area of research which lack the glitz and glamour of projects that claim to have produced a digital 'twin' for a chosen application, and subsequently makes them less of an attractive proposition for funding and subsequent research. However, it is this that will hamper the development of digital twins. To an outsider, the existence of demonstrator projects makes it looks like the art of the possible has been showcased, when the reality in most cities is very different. Moving forward, work needs to be done to ensure that there is a common practice for generating and managing big data sets so that it is open and interoperable for digital twin technology. Next steps for future urban sensing efforts need to be designed to ensure longevity, rather than the current trend of siloed thinking and project-based design. To promote the future use of sensors for digital twins governance will be key. This involves both bridging digital and data skills gaps within stakeholders and relevant sectors through education and creation of specialist job roles and by championing data standards for sensor live streams (Chapman et al., 2023a,b; Department for Education, 2021).

Overall, there is huge value, if interpreted correctly, in the outputs of low-cost sensors. Their accessibility is leading to data densification, via citizen science, enhanced research outputs and government monitoring using these sensor types. The improvements live stream data can enable in decision making cannot be under-estimated; live air quality data has potential to decrease health risks from pollution exposure by supporting decision making throughout various time scales. The creation of open-source data visualization can support data use, by simplifying data for use in forecasting, real time analyses and communication (Chapman et al., 2023a,b). Planning will be enhanced by the dynamic nature of digital twin technology, which allows for complex testing of potential air pollution mitigation efforts with the integration of real-world data feedback. At shorter-term, rapid-fire decision making by technology will be able to optimize real-time air quality management within the changing conditions of a city environment to reduce inhabitants' exposure. Traffic will be able to be managed with not just journey time in consideration, but also current and predicted pollution concentrations, meteorology and surrounding traffic flow, although this will require the embedding of more complex traffic data in the longer term. A range of stakeholders will be able to dynamically experiment with different urban planning and management interventions, improving solutions and buy-in to them.

Recommendations and guidance for enabling sensors to support air quality management via digital twins include:

- Networks that integrate an array of live stream data (not just air pollution observations) will give a holistic insight into urban air pollution and are best placed to be integrated into digital twins.
- There is a lack of easily accessible information about what live stream data exists in cities globally. A detailed catalogue of live streams will help identify the potential of urban digital twins in a city.
- When using 'sensing as a service', ensure sensor providers chosen promote open access to both data and metadata to ensure reliability, transparency and usability of data live streams.
- There is a pressing need to identify and develop standardized approaches to managing urban data live streams and metadata to promote interoperability.
- Recognizing that progress will likely comprise of building blocks of much smaller sector, purpose or location specific digital twins, which if designed to be interoperable and open access, can later be integrated as bigger connected twin.
- Promote cross collaboration between research, data science, public sector and citizen scientists. Whilst there are digital skills gaps in the public sector, research engagement into non-academic projects that create urban data live streams could help overcome this.

Notwithstanding the barriers presented, if AQ digital twins become mainstream, consideration also needs to be given to the underpinning durability of such networks. Whilst there is a plethora of open-access sensor networks available to gather environmental data from, many of these were deployed with a single purpose or aim by the end user. This often means that when this aim is met, or a project comes to a close, the sensors are retired due to lack of ongoing funds or platforms to host data. Data streams need to be reliable and the collapse of streams like this will limit capability of digital twins. To ensure digital twins for air quality meet their full potential, there will need to be a shift from demonstrator and project-based sensor deployment to legacy and collaborative deployments which ensure data stream longevity. Next steps will include considering scalability will be vital to ensuring a transitions from project digital twins, to city and then nationwide scales twins. Scaling up digital twins will need longer term more strategic approaches to monitoring that go beyond simply deploying sensors on a project by project basis.

Author contributions

NC: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. LC: Conceptualization, Funding acquisition, Investigation, Project administration, Supervision, Writing – review & editing. DT: Conceptualization, Funding acquisition, Investigation, Resources, Writing – review & editing. PJ: Conceptualization, Funding acquisition, Investigation, Resources, Writing – review & editing. DB: Data curation, Investigation, Methodology, Project administration, Writing – review & editing. TB: Data curation, Investigation, Methodology, Project administration, Writing – review & editing. EM: Data curation, Investigation, Methodology, Project administration, Writing – review & editing. JE: Investigation, Writing – review & editing. MB: Investigation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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