**TITLE**

The sensor desert quandary: What does it mean (not) to count in the smart city?

## **ABSTRACT**

As a central component of the smart city, sensor infrastructures locate and measure a wide range of variables in order to characterise the urban environment. Perhaps the most visible expression of the smart city, sensor deployment is a key equity concern. As new sensor technologies and resultant data interact with social processes, they have the potential to reproduce well-documented spatial injustices. Contrary to promises of providing new knowledge for cities, they can also create new gaps in understanding about specific urban populations that fall into the interstices of data collection—what we term *sensor deserts*. Building upon emerging data justice debates, specifically considering distributional, recognition and procedural forms of injustice, we conceptualise and analyse sensor deserts through two case studies, Newcastle’s Urban Observatory (UK) and Chicago’s Array of Things (US). Open sensor locations are integrated with small-area socio-economic data to evidence the demographic configuration and spatialities of sensor deserts across each city. We illustrate how the structural processes via which inequality is reinforced by smart agendas manifest as uneven social and spatial outcomes. In doing so, the paper opens up a new conceptual space in which to consider what it means (not) to count in the smart city, bringing a demographic perspective to critical debates about smart urbanisms.

## **KEYWORDS**

*Sensor desert, smart city, spatial inequality, data justice, recognition.*

## **ACKNOLWEDGEMENTS**

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DATA AVAILABILITY:

The datasets and code underpinning the descriptive analysis in the paper are available here: [*https://github.com/CaitHRobinson/SpatialInequalityintheSmartCity*](https://github.com/CaitHRobinson/SpatialInequalityintheSmartCity)

**1. INTRODUCTION**

More data is being produced than ever before, with approximately ninety percent of the data available today generated during the last two years. Seeking to mobilise this wealth of data to inform urban decision-making, smart cities have been heralded as a leading driver of regeneration and sustainability. Central to smart cities, sensor technologies collect and stream real time data and are subsequently big business. During 2020 cities will spend $20 billion on sensor technologies (Navigant Consulting, 2018). Paradoxically, in many national contexts, expensive and expansive smart city agendas have emerged during an era of post-2008 crisis austerity and growing global and regional inequality. Three quarters of cities are now more unequal than during the previous decade, despite unprecedented wealth generation (UN-Habitat, 2016).

Whilst pitched as a solution to a range of challenges driving urban inequality in the Global North, including the piecemeal growth of infrastructures, ageing populations, climate change and cuts to public funding, smart urbanisms are highly geographically uneven, with the potential to further splinter the city into smart enclaves and less connected areas (Shelton et al. 2015). Scholars have critiqued the neoliberal (Ho, 2017), technocratic (Kitchin, 2014), individualising (Vanolo 2014), and securitizing (Gabrys, 2014) aspects of smart cities. Although powerful in illustrating the structural processes via which inequality is enhanced by smart agendas, these broader debates offer less of a sense of how these processes manifest as uneven social and spatial outcomes (Hoffmann, 2018). With the smart city increasingly ubiquitous, and as many of the imaginaries floated during the last decade have begun to be realised, now is an appropriate time to take stock of the role of smart urbanisms in the alleviation, maintenance or propagation of spatial inequalities that have long been a feature of cities.

This paper focuses upon inequalities embedded within one of the most visible expressions of smart city activities, sensor networks, specifically considering deserts in sensor coverage and subsequent data collection. Whilst critics have voiced legitimate concerns about smart-surveillance (which also produces gaps in coverage, albeit arguably in favour of the “un-counted”), emphasis upon a lack of coverage allows us to consider what might be thought of as the antithesis of over-surveillance, asking instead what it means *not* to count in the smart city. Differentials between people and places that are counted and those who are not have long attracted attention, highlighting the ways in which numbers are used to govern via highly politicized processes of social quantification (Rose, 1991; Beer, 2016). Similarly, as new sensor technologies interact with social processes, they have the potential to reproduce well-documented social and environmental injustices (Safransky, 2019). Despite aiming to produce new data and knowledge about cities—gaps in understanding about specific urban populations also emerge, what we term *sensor deserts*. Although sensor networks tend to give the impression of ubiquity across an urban environment, in fact, networks are discrete and some neighbourhoods and places will necessarily be covered while others are not. Sensor deserts then are a smart-specific form of inequality, spatially concentrated in areas that lack coverage and therefore the investment, representation and legitimacy associated with smart city agendas.

We conceptualise sensor deserts based on a preliminary analysis of two case study smart cities that provide open, real-time, urban data and are primarily publicly funded: Newcastle’s Urban Observatory (UO) and Chicago’s Array of Things (AoT). Sensor locations are combined with socio-economic and demographic datasets to offer insights into potential sensor deserts. Our approach necessitates a normative assumption that coverage is generally positive, based on the idea that all groups are equally entitled to sensor coverage. This means that we cannot account for the local politics of resistance to technologies by communities, owing not least to concerns about privacy and surveillance that are often highly racialized (Browne, 2015; Jameson et al. 2019; Brayne, 2017). These nuances are almost impossible to capture using quantitative datasets. However, our analysis succeeds in illustrating how wider structural processes via which inequality is enhanced by smart agendas manifest as uneven social and spatial outcomes at a neighbourhood scale. In bringing a demographic perspective to critical debates about smart urbanisms we open up new conceptual space in which to consider what it means (not) to count in the smart city.

The paper is structured as follows. In Section 2 we review evidence of the uneven geographies of smart cities. This is followed by a framing for understanding spatial inequality in the smart city building upon data justice debates. We focus on three types of injustice—distributional, recognition and procedural (see Walker and Day, 2012)— reflecting on their application to smart cities (Section 3). Section 4 discusses in greater detail the concept of sensor deserts. Our analytical approach and datasets, a spatial analysis of sensor locations and demographic datasets, are then introduced (Section 5), followed by presentation of two case studies (Section 6). The triad of injustices structure our discussion, illustrating how sensor deserts are a problem of uneven distribution, or lack of recognition and procedure (Section 7). We conclude on a hopeful note, with suggestions for policymakers and smart cities researchers, while situating our study within its wider context of spatial inequality and urban research.

**2. THE UNEVEN GEOGRAPHIES OF SMART CITIES**

There are many different definitions of what it means for a city to be smart, and in turn of who or what the smart city might be for (Caprotti and Cowley, 2019). In the case of flagship agendas driven by Big Tech ‘it is hard to imagine how…[such cities] would benefit anyone but the ultra-elite’ (Phinney and Nicolussi, 2019). Meanwhile, the ‘actually-existing smart city’ recognises that most interventions are the outcome of data-based policy initiatives that must be awkwardly integrated into existing urban governance structures (Shelton et al. 2015). Enacted by local government and private sector actors, such projects must balance often-conflicting aims of promoting economic growth versus providing solutions to social problems. Whilst many of these examples engage with the public in what Levenda et al. (2020) describe as a tokenistic way, bottom up approaches to smart urbanisms also exist as evidenced by Odendaal (2016) in Cape Town, South Africa. These wide-ranging examples of smart cities each grapple with the geographies of the place in which they are enacted (Watson, 2015), whilst simultaneously shaping the production of space locally.

For Dalton et al. (2019), smart cities, and the data they produce, tend to naturalise the constructions of space that characterise the governance structures on which they are built. Smart technologies and infrastructures subsequently divide and polarise cities at multiple scales, reproducing historically and geographically embedded patterns of privilege whilst simultaneously creating new geographies of inequality (Shelton et al. 2015). The fragmentation of the city by networked infrastructures into ‘haves’ and ‘have-nots’ is by no means a new idea. Graham and Marvin (2002) outline splintering urbanism, a process via which networked infrastructures have created selected powerful spaces as they are privatised and liberalised. Processes of splintering are also ongoing in the smart city. In the case of India’s recent 100 smart cities initiative, democratic governance processes have been weakened resulting in ‘splintered infrastructure development that benefits the wealthy, further marginalizing the poor’ (Das, 55: 2020).

Subsequently, smart city projects intersect with, and intensify existing socio-economic inequalities, reinforcing patterns of exclusion for marginalized groups (Benjamin, 2019). This is evident in Safransky’s (2019) exploration of algorithmic violence, defined as ‘a repetitive and standardised form of violence that contributes to the racialization of space and the spatialization of poverty’. Here, algorithms that help city officials to make decisions about which neighbourhoods will receive investment have further entrenched existing patterns of racialised segregation generated by historical ‘redlining’ policies in US cities, enhancing highly racialized processes of austerity urbanism (Phinney, 2019). Smart cities also have the potential to generate new forms of spatial inequality. Shelton and Clark (2016) recognise how despite a perception that smart city agendas will encompass the whole urban area, the creation of test bed districts has often been encouraged. This bite-size approach is advocated for as more manageable, yet risks reinforcing and reproducing socio-spatial fragmentation (Leszczynski, 2016). New smart enclaves are generated, places that are highly connected both within their boundaries and to quite distant places, but that are distinct from neighbouring areas that lack advanced connectivity. Furthermore, funding agencies increasingly push limited resources to such data-rich areas. In response to these uneven geographies, a language of ‘justice in’ (Taylor, 2017; Dencik et al. 2019) or ‘a right to’ (Kitchin et al. 2019) the smart city has emerged.

**3. SMART INJUSTICES: DISTRIBUTION, RECOGNITION AND PROCEDURE**

There is increasing concern about the power dynamics entangled with the datafication of society (Datta and Odendaal, 2019). In response, data justice ensures fairness and equity in the ways in which people are made visible and represented during the production of digital data (Taylor, 2017). Fundamental to data justice is a socio-technical understanding of technology, decentring the technical to understand the associated socio-economic, political and cultural issues (Dencik et al. 2019; Pena Gangadharan and Niklas, 2019). A socio-technical approach reflects how processing of data from across our lives fundamentally shapes social relations. On the one hand, data influences what is knowable, and acted upon. On the other, data is the product of an amalgamation of different actors, interests and social forces. Further extending the concept of data justice, debates about the ‘right to the smart city’ emphasise that if the smart city is to be just and equitable, it is ‘not merely a right of access to what already exists, but [crucially] the right to change it’ (Kitchin et al. 2019, citing Harvey 2003). These debates can be extended to encompass the sensor technologies that collect, and shape, increasing volumes of data.

To understand the processes via which the socio-spatial inequalities are bound up with the smart city, various established concepts of justice have been drawn upon, including distributional and procedural justice (Kitchin et al. 2019). These two concepts highlight inequalities in the distribution of benefits of the smart city and involvement in decision-making processes. Additionally, we add to this list recognition justice, concerned with ensuring that the needs of all groups are sufficiently acknowledged (Fraser, 1995; Michalec et al., 2019). The framework allows the ‘institutionalised exclusion, social culture of misrecognition and current [uneven] distribution patterns’ (Schlosberg, 2004: 518) potentially associated with smart cities to be confronted, including sensor deserts.

Distributional injusticecan be described simplistically as ‘who gets what’. The idea of distribution is central to any justice claim and can be considered a somewhat classical understanding of the elimination of inequalities (Honneth, 2004). The term reflects perceived fairness or equality in how benefits and burdens are shared by, or distributed across, different members of society. Examples of distributional injustice in the smart city include the uneven distribution of infrastructures, public resources and funding, or subsequent policymaking.

Recognition injustice is concerned with accommodating the needs of groups that are not sufficiently recognised (Fraser, 1995). Recognition acknowledges that certain groups are not given the respect and rights afforded to others. The term concerns the acknowledgement of a diverse range of outlooks that are intertwined with social, cultural, ethnic, racial and gender differences. Examples of recognition injustice include the systematic lack of engagement with communities with the smallest political voice, often the most exposed to urban challenges (e.g. climate change impacts), and the reification of data emerging from incomplete sensor networks.

Procedural injustice attends to the way in which distributional inequality is produced and sustained (Young, 1990). This includes meaningful participation in decision-making, as well as access to information and legal processes to challenge decisions. Examples in the smart city include a lack of diversity in its design and formulation, or the inability to make use of, or mobilise around, outputs. Concepts of distributional, recognition and procedural injustice can underpin analysis of spatial inequality in the smart city, including sensor deserts.

## **4. THE SENSOR DESERT QUANDARY**

For Konga (2017), ‘smart is sensor fed’. Sensors collect data to characterise the urban environment at a higher spatio-temporal resolution. This characterisation can be applied to ensure operations run more efficiently, improving services for citizens whilst reducing government costs. Spatially, sensors are part of a wider decentralisation of increasingly small yet networked computers that allow for the collection of a greater volume, variety, and velocity of data (Batty 2013). Building on the socio-technical understanding that underpins data justice debates, these sensor technologies (and subsequently the data they collate) are shaped by complex and often locally specific priorities, actors, and social relations. Sensor deserts are a smart-specific form of inequality produced by these socio-technical arrangements, spatially concentrating in areas that lack sensor coverage.

With sensor technologies increasing in volume and ubiquity, a variety of sensor deserts become apparent in both the physical sensor infrastructures and the data produced. Whilst many of the components of the smart city are hidden from view in offices or the cloud, sensor infrastructures have a visible, material presence in cities, attached to lampposts or installed on kerbsides. Their deployment is indicative of investment priorities, and therefore which people and places are represented and legitimised by smart city efforts. Decisions about the placement of sensor infrastructures also shape the gaps and subsequent biases in the data that is collected. Crucially, sensors cannot provide ubiquitous coverage of all areas—without attendant uncertainty in data quality—and are necessarily selective in terms of placement.

Subsequently deserts by data—the spatial imprint or footprint of places that fall into the interstices of sensor data collection—also emerge. Deserts in data are by no means a new phenomenon and there has long been interest in the ways in which people and places are made (in)visible by statistics (Rose 1991; Beer, 2016). The US census undercount is a typical example of this, with the worst undercount in three decades forecast for the 2020 census. Four million people risk being missed from estimates, particularly affecting African American (-3.68%) and Hispanic (-3.57%) populations (Urban Institute, 2019). Despite claims of increasingly ubiquitous sensing infrastructures, smart cities have created a ‘data deluge’ in some domains whilst ‘data deserts’ continue to exist (Kitchin, 2014: 3).

In practice, sensors are broad in both their definition and scope, with implications for what constitutes good coverage. They must balance competing demands from different stakeholders and communities with technical practicalities, with implications for what constitutes good coverage. A market-based logic is likely to result in the deployment of sensors in the most lucrative neighbourhoods (Shelton et al. 2015). Placement may also be politically motivated, with civic leaders knowing which areas need to be “bought off”. Those concerned with social justice are more likely to locate sensors equitably, either in neighbourhoods most exposed to negative impacts of urban challenges or amongst populations that are physiological vulnerable to hazards. Relatedly, for the purpose of representation, even coverage across the city might be most desirable. Sensor networks are also shaped by the potential for modelling that interpolates values for areas without sensor coverage, based on data derived from other neighbourhoods—although as noted above, interpolated values carry uncertainty measures with them and so the question remains: for whom do sensors produce (accurate) data? Meanwhile, the complexity of the urban environment in which sensors are placed determines the degree to which a sensor is representative. Each of these aspects has implications for sensor locations, and what they subsequently capture and emphasise. As such, there are multiple ways of conceptualising sensor deserts (Table 1).

**Table 1.** Sensor desert conceptualisations

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Sensor desert type** | **Sensor network function** | **Desert identification** |
| **Network purpose** | Hazard-orientated | Coverage of hazard/nuisance producers (e.g. sources of pollution) | Places without sensors in which there are known hazards |
| Vulnerability-orientated | Coverage of populations disproportionately at risk of negative impacts from hazard (e.g. elderly or very young) | Residential or mobile populations without sensor coverage |
| **Measurement type** | Material | Political: Visibility of sensors signalling representation | Neighbourhoods or wards lacking sensors |
| Utilitarian | Evidence-based: Sensors produce information for the catchment area or “footprints” in close proximity to sensors | Locations falling outside sensor catchment areas |
| Technical | Evidence-based: Sensors function as inputs to models, which generate estimated values for all urban locations | Locations with high levels of uncertainty around estimated values |

## **5. ANALYTICAL APPROACH AND DATASETS**

A key cartographic challenge is illustrating where spatial data observations are missing, and analysing variables indicative of absence (Robinson, 2017). To identify sensor deserts in our case studies, we focus on material and utilitarian approaches to measuring sensor deserts (Table 1). Locations of sensors are combined with a range of socio-economic and demographic data representative of different inequalities using descriptive spatial analysis techniques. Although we consider a range of sensor types, detailed analyses focus on air quality sensors given the clear link to policies that benefit all of society, although similar challenges also apply to traffic, noise, and temperature, for example.

### **5.1. Analytical approach**

By taking a material and utilitarian approach to measurement, we assume that if a small area contains a sensor then it has coverage to some degree, limiting our understanding in several ways. This binary approach underestimates the complexity of sensor technologies and the data generated, given that different types of sensors vary in their scales of measurement. We cannot account for diversity within each small area, or its size, and therefore the extent to which a single sensor is representative of that setting. The approach also does not account for areas that contain more than one sensor. These assumptions are necessary owing to the constraints imposed by the boundaries for which administrative datasets are available. To overcome some of these constraints, analyses of distance to the closest sensor are conducted using a *Distance-to-Nearest-Hub* technique. A straight-line distance is calculated between a Population Weighted Centroid (PWC) (representative of the distribution of the population in each area) and the nearest sensor (ONS, 2011a.). Our analysis does not consider more technical approaches to sensor placement, i.e. we do not consider sensor deserts that result from a network designed to be input into a model, and the uncertainty associated.

### **5.2. Data**

Sensors are generally represented by points at which real-time data is collated. For the UO and AoT, networks continuously evolve as new sensors are added. We combine sensor locations with socio-economic and demographic datasets (Table 2), which are chosen to represent structural forms of disadvantage (e.g. racial inequality, income or deprivation) or physiological vulnerabilities to specific hazards (e.g. age-related); certain datasets reflect the inequality embedded in sensor technologies themselves (e.g. internet access). The list is not intended to be exhaustive but rather illustrative of the diversity of potential sensor deserts in different contexts.

Datasets are mapped in deciles relative to the country of interest. For example, the median income dataset for Chicago shows which census tracts have an income amongst the 10% lowest relative to the median income across the US.[[1]](#footnote-1) In Newcastle, data are available at the Lower Super Output Area (LSOA) scale representing approximately 1,500 persons (ONS, 2011). In Chicago, data is broken down by census tracts[[2]](#footnote-2) that encompass between 2,500 and 8,000 people (IPUMS, 2019). Results should be understood as context-specific and direct comparison between the case studies is discouraged.

For Chicago, datasets are derived from the US 2010 census and the American Community Survey (IPUMS, 2019)[[3]](#footnote-3). For Newcastle, in addition to datasets derived from the UK 2011 Census (ONS 2011b.), two datasets merit further exploration. Firstly, the English Indices of Multiple Deprivation (IMD) are a measure of relative deprivation calculated every five years that is well understood by policymakers. The IMD is comprised of seven domains assigned varying weights: Income, Employment, Disability and Health, Education and Skills, Barriers to Housing and Services, Living Environment and Crime (DCLG, 2015). Secondly, the Internet User Classification (IUC) is a geodemographic indicator that describes how people interact with the internet (Alexiou and Singleton, 2018). A dataset of state-funded primary schools and their rating is also created.

**Table 2.** Selected datasets

|  |  |  |
| --- | --- | --- |
| **Dataset** | **Format** | **Source** |
| **Newcastle (UK)** |  |  |
| Index of Multiple Deprivation  Disability and health (day-to-day activity limited) | Deciles relative to England | DCLG (2015)  ONS (2011) |
| Ethnic group |  | ONS (2011) |
| Young persons (0 – 7 years) |  | ONS (2011) |
| Older age (65 years and over) |  | ONS (2011) |
| Private renters  Social renters |  | ONS (2011)  ONS (2011) |
| Internet User Classification | Categorical variable | Alexiou and Singleton (2018) |
| **Chicago (US)** |  |  |
| Medium Income  Race: African American | Deciles relative to US | IPUMS (2019)  IPUMS (2019) |

**6. MAPPING SENSOR DESERTS IN THE SMART CITY**

The analysis that follows focuses on two case studies, Newcastle UO and Chicago AoT. Both are examples of what Shelton et al. (2015) term ‘the actually existing smart city’, engaging a variety of public and private actors to integrate smart technologies into the existing urban environment. As publicly funded networks that are committed to producing open data for social good, UO and AoT merit evaluation from an equity perspective. The UO and AoT were selected as case studies because they are two of the largest open sensor networks, and represent best practice compared with smart cities in which data is inaccessible, or behind a paywall. These case studies are some of the only networks that can be systematically analysed in this way, opening themselves up to critical interrogation; they are also widely recognised as prototypical smart city examples, and thus it is particularly valuable to consider what lessons they may impart for other cities following in their footsteps.

### **6.1. Newcastle’s UO**

First, we turn our attention to Newcastle, the largest city in the north east of England with a population of 293,000. Situated on the River Tyne and forming part of the wider conurbation of Tyne and Wear, Newcastle was a centre for shipbuilding and coalmining during the Industrial Revolution. The decline of these industries led to increasing levels of unemployment during the 1980s, shaping present day patterns of inequality. Currently, 22.3% of LSOA in Newcastle rank in the 10% most deprived nationally (DCLG, 2015). Since 2008, cuts to local government funding have hit disproportionately hard and the gap between the highest and lowest earners has grown (NIHS, 2018).

Operating within this context, the UO is an ambitious £2 million smart city investment representing the largest public, real-time dataset in the UK. The UO aims to provide ‘evidence for change’, collecting data from 1491 sensors across the region related to 60+ variables including traffic, air quality, weather, noise and water quality (correct as of August 2020) (UO, 2019). Decisions about sensor placement in the UO network were made on a relatively ad-hoc basis, in response to local government policy priorities, fragmented funding pots targeted at specific issues, or specific requests from local advocacy groups. Due to the wide geographical scope of the UO, we focus on the Local Authority (LA) of Newcastle upon Tyne which is composed of 175 LSOA and contains 657 of the sensors deployed to date. Figure 1 maps the distribution of air quality sensors across Newcastle upon Tyne LA, according to multiple derivation. As we might expect, five neighbourhoods in the city centre are ‘data-rich’ with a high density of air quality sensors (Shelton et al. 2015). Neighbourhoods to the north east of the centre also have a relatively high concentration of sensors. Meanwhile, areas without sensors are what we term sensor deserts—these areas are less likely to have sensor data and knowledge produced for them.

**Figure 1.** Air quality sensor distribution and multiple deprivation in Newcastle.

**Data source:** UO (2019), DCLG (2015)

A picture containing text, map

Description automatically generated

Inequality in coverage according to multiple deprivation varies between sensor types (Figure 2). Considering traffic or vehicle sensors, distribution is relatively equitable, with similar coverage (approximately a quarter of LSOA) for areas in the most deprived 20% and least deprived 20% of neighbourhoods, relative to the rest of England. Conversely for other sensor types, affluent LSOA are more likely to contain a sensor, a trend that is particularly stark for air quality, weather and noise. LSOA in the least deprived decile are approximately eight times more likely to have a noise sensor compared to the most deprived decile, and 4.5 times more likely to have an air quality sensor.

**Figure 2.** UO sensors broken down by sensor type and multiple deprivation.[[4]](#footnote-4)

**Data source:** DCLG (2015), UO (2019)



Focusing on air quality sensors and multiple deprivation, a similar pattern continues with typically shorter mean distances to a sensor in relatively affluent areas (Figure 3). None of the five most deprived areas (in Walker, Byker, Benwell, Cowgate and Elswick) contain a sensor, despite containing a major A-road with the potential for high concentrations of pollutants. However, neighbourhoods with a high proportion of ethnic minority or privately rented households are closer to a sensor. These demographics concentrate close to the city centre where there is a higher level of coverage. Meanwhile, generally the higher the proportion of social housing the greater the average distance to the nearest sensor: LSOA in the highest 10% are on average 926 metres from the nearest sensor, compared to 691 metres in the lowest 10%. Where physiological vulnerability of young children and older persons to poor air quality is concerned, the picture is more varied. Neighbourhoods with a low proportion of both populations are likely to be closest to a sensor.

**Figure 3.** Distance to nearest air quality sensor broken down by socio-economic datasets.

**Data source:** DCLG 2015, ONS 2011

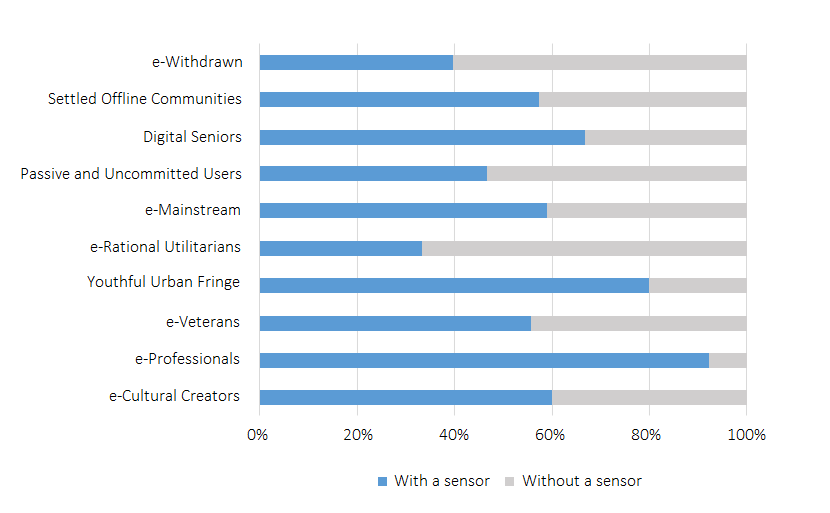


Investigating young populations in greater detail, through several UO funding sources and engagement initiatives, 21 of the 73 state-funded primary schools have had an air quality sensor installed during the life time of the network. This represents approximately 26% of primary school aged children in the LA and, to our knowledge, the most extensive coverage of schools with air quality sensors in the UK. Distributing sensors by schools has resulted in a relatively equitable distribution where deprivation is concerned, with schools located in LSOA in each decile allocated a sensor. However, considering Ofsted assessments that indicate school quality, those allocated a sensor are ranked either “Good” or “Outstanding”, while schools assessed as “Requires Improving” or “Inadequate” are all sensor deserts.

Further to issues of representation of different communities, inequalities in the ability of different groups to use the data produced by the network of sensors are also apparent, as evidenced by deserts in coverage amongst different types of internet user. The IUC is indicative of how confident communities are engaging with new technologies or accessing data. Large swathes of LSOA are classified as e-Withdrawn, with high numbers of individuals who have no internet access or low levels of engagement. e-Withdrawn areas are typically less affluent, and have high levels of ethnic diversity, unemployment, and social housing (Alexiou and Singleton, 2018). Sensor deserts are most common in e-Withdrawn areas, where 39.5% contain a sensor (Figure 4). Meanwhile, e-Professional areas characterised by high levels of internet engagement have the greatest sensor coverage (92.3% of LSOA). Typically, highly qualified, young and ethnically diverse, e-Professionals concentrate in or near the city centre, or in affluent suburbs.

**Figure 4.** Air quality sensor coverage using IUC

**Data source:** Alexiou and Singleton (2018)[[5]](#footnote-5)



**6.2. Chicago’s AoT**

Chicago, Illinois, is the third most populous city in the US, with approximately 2,705,994 inhabitants. The city is an international hub for finance, culture, and technology, yet stark inequalities exist. Chicago is one of the most racially divided cities in the US and historical processes of segregation are visible in its geography, with clearly defined racial boundaries between neighbourhoods. As such, deeply entrenched urban problems are highly racialized (Sampson and Winter, 2016). Conversely, Chicago has ranked highly in smart city indexes and the current Mayor has ambitions to make the city ‘the most data-driven government in the world’ (HEREMobility, 2019).

Situated within these wider urban and political structures, Chicago’s flagship AoT collects real-time data for research activities and public use (AoT, 2019). A range of universities, local government and communities makes decisions about the development of a network composed of 126 nodes (correct as of August 2020). Each node contains several sensor types including temperature, light and pollutants. The network is incomplete and once fully implemented will consist of 500 nodes—subsequently observed patterns of inequality are likely to change.

Chicago is comprised of 801 census tracts[[6]](#footnote-6). In the absence of a deprivation indicator, sensor coverage according to median income and racial composition is mapped (Figure 5). Median income is low across the city, with 18.3% in the lowest decile (below $29,081) relative to the rest of the US. Sensor coverage according to the AoT network is most comprehensive for the highest median income decile ($101,489–$250,001) with 16.7% of census tracts containing a sensor (Figure 6). However, this is closely followed by the second lowest decile ($29,081–$36,698) in which 15.13% of census tracts contain a sensor. Deciles with relatively high and low median incomes tend to have the greatest coverage.

Mapping coverage according to racial composition of census tracts helps to visualise the enduring racial segregation between neighbourhoods (Figure 6). The proportion of the population identifying as African American in selected tracts is 99%, whilst others record a figure of 0%. In the AoT network, tracts characterised by a high proportion of African American groups are more likely to have a sensor than predominantly white tracts. This distribution somewhat contradicts the racial disparities embedded within urban inequalities in Chicago. There are however, likely sensor deserts which merit further attention in Chicago related to ethnicity that this analysis does not consider. Recent analyses of environmental pollution burdens highlight industrial corridors in Chicago’s Southwest and Southeast Side (NRDC, 2018). Characterised by largely low income, Hispanic communities, these areas have relatively low sensor coverage.

**Figure 5.** Medium income and African American population in Chicago as a whole (left) and those with sensor coverage (right). Variables are classified in deciles.

**Data source:** IPUMS (2019).

**Figure 6.** Sensor coverage for Chicago according to median income and African American population.

Variables are classified in deciles.

**Data source:** IPUMS (2019).

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**7. SENSOR DESERTS AND THE PRODUCTION OF INJUSTICE**

Having provided examples of sensor deserts, we now interpret the results considering distributional, recognition and procedural injustice (Table 3). Each has implications for how people come (not) to count in the smart city.

**Table 3.** Types of injustice and their application to sensor deserts

|  |  |  |
| --- | --- | --- |
| **Concept** | **Definition** | **Application to sensor deserts** |
| **Distributional injustice** | Equality in how benefits and burdens are shared by, or distributed across, society (Honneth, 2004) | * Inequitable distribution of sensor infrastructures * Lack of knowledge produced for particular groups or places: exposure to, e.g., poor air quality potentially under-estimated for vulnerable groups Further compounded if scarce public resources are allocated based upon uneven sensor data |
| **Recognition injustice** | Certain groups not having the respect and rights afforded to others, meaning they are not sufficiently recognised  (Fraser, 1995) | * Systematic lack of measurement in certain areas impacting upon those with least voice, often most exposed to urban challenges * Lack of diverse representation in the design of smart cities * Reification of data emerging from incomplete sensor coverage and subsequent modelling |
| **Procedural injustice** | Processes that produce and sustain distributional injustices, including participation in decision-making, and access to information or legal processes to challenge decisions  (Young, 1990) | * Inability to make use of, or mobilise around, evidence produced * Incomplete data produced omits affected groups from decision-making, because they were never measured * Risk of smart cities de-responsibilising local and national governments, placing responsibility for acting on the data produced on the individual. |

**7.1. Distributional sensor deserts**

Investment in sensors can make visible distributional injustices in the city, for example, geographic concentrations of poor air quality or high volumes of traffic. Yet, the uneven deployment, socially or spatially, of sensors is also a form of distributional inequality, rendering invisible or uncounted the places that are not measured. Where we identify sensor deserts, a lack of coverage means that data is not collected, and less is known about localised urban dynamics, especially processes that are relatively complex to model.

Typically, smart city narratives, and therefore sensor distribution, have been understood as replicating existing infrastructural divides along deprivation, class and racial lines (Benjamin, 2019). Distributional inequalities owing to sensor deserts are further compounded when equality should have led to certain groups and places being prioritised for measurement. For example, Barnes and Chatterton (2017) evidence how areas with a high proportion of young persons and poorer households tend to have high concentrations of traffic-related pollution; they are therefore likely to have the greatest need for adequate coverage.

Our case studies suggest that, in practice, the distribution of inequality in the smart city is highly complex, varying case-by-case depending on the type of inequality prioritised. Neither focus solely on ‘data-rich test beds’, symptomatic of many smart city initiatives (Shelton et al. 2015). Newcastle UO is relatively successful when it comes to physiological vulnerability, achieving a high level of air quality sensor coverage of primary school age children, ethnic minorities, and privately rented households. Even so, affluent areas tend to be prioritised for most sensor types. In Chicago, tracts characterised by a high proportion of African American population are most likely to have a sensor, contradicting the assumption that sensor infrastructures will replicate entrenched, racial disparities in the city. The network is therefore more likely to make visible environmental injustices, predicated upon racial divides (NDRC, 2018).

The case of Newcastle also exemplifies the importance of understanding the local context when analysing sensor deserts. Somewhat at odds with established environmental justice research (Barnes and Chatterton, 2017), some of the most affluent areas of Newcastle have poor air quality. In the suburb of Gosforth, two areas that flank one of the main arterial roads rank amongst the 10% least deprived. Here 30+ sensors are deployed, representing the most geographically concentrated coverage outside the city centre. Yet, readings of over 100 ugm-3 of N02 evidence sustained high levels of pollutants. Thus, concerns of equality according to typical geographies of exposure to poor air quality are turned on their head.

One explanation of distributional inequalities made visible by our case studies is the competing claims to smart-ness made by different actors. Diverse stakeholders have different views about how the potential benefits of increasingly sophisticated understanding of cities should be distributed. Decision-making tends to be governed by a relatively ad-hoc and fragmented funding landscape that restricts systematic consideration of equitable coverage. Instead limited resources often focus upon hazards of immediate concern. For example, in Newcastle, the distribution of air quality sensors reflects ongoing proposals for a Clean Air Zone to ensure compliance with European legislation. The targeted nature of sensor placement also has wider equity implications related to the displacement of urban ills. By only installing sensors in areas with a greater propensity to a particular urban hazard, policy-makers are unlikely to be able to evaluate the future implications of alleviation measures which may in fact shift a hazard to other, less sensor-ed, areas of the city. This is evidenced in shifts in traffic to residential streets by the real-time, crowd-sourced app *Waze* (Bliss, 2015).

Future distributional inequality concerns emerge when we consider the channelling of scarce resources into smart cities, especially when infrastructures are publicly funded or rely on the resources of community or local government actors, true for both of our case studies. A troubling paradox has emerged of funds being mobilised for smart cities, whilst simultaneously reducing spending on public services (Pollio 2015). Indeed, the smart city should not be a replacement for integral public services that underpin an equitable city. However, if resources and funding are scarce, consideration must be made about how best they can be used. As such, we now turn our attention to recognition and procedural injustice.

**7.2. Recognition sensor deserts**

Arguably, smart cities represent an opportunity for greater diversity and inclusivity in urban design. In practice, Vanolo (2014: 893) argues that ‘there is little room for the technologically illiterate, the poor and, in general, those who are marginalised’. Selected groups, particularly low income or ethnic minority, are often stigmatised for their disproportionate reliance upon the welfare state or purported difference, in turn reducing engagement with political processes (Lamont, 2018). Transient demographics—for example, private renters and students—are often less invested in their area (Burrell, 2016), lacking representation in local decision-making. If this translates into a systematic lack of measurement amongst demographics with the smallest politic voice, urban challenges specific to those people and places risk being obscured.

Recognition inequality can also be perpetuated by the reification of data produced by sensor technologies (Mattern, 2013). Reification refers to the error of treating something that is not complete as concrete. The concept has been used to critique the tendency for smart city decision-makers to assume they can offer a technical solution to all problems. Without careful thought, understanding of complex social processes can be over-simplified (Leszcynski, 2016). Examples of the process of reification are evident in the ambition of smart cities to provide an all-encompassing understanding of the urban. Sensors typically provide data representative of a small radius (e.g. 50 metres), yet the analysis and display of data can imply understanding of a process for the entire area, presenting data as a surface despite incomplete socio-spatial coverage. Such misclassifications disproportionately impact marginalized groups, rendering them less visible (Peña Gangadharan and Niklas, 2019). This necessitates modelling of values for areas without sensors, based on data derived from areas with different characteristics. Whilst neither Newcastle nor Chicago claim to provide a complete urban picture, recognition inequality associated with reification of incomplete coverage should be considered when modelling using sensor data.

In practice, recognition-based inequalities are evidenced to differing degrees in each case. In Newcastle, post-industrial areas along the River Tyne that lack sensor coverage are characterised by high levels of deprivation, ethnic minority populations and low levels of home ownership, typical of wider understandings of gaps in recognition (Lamont, 2018). Despite ongoing discussions about age-friendly cities, recognition injustice is also likely to affect older age groups underrepresented within the network. In Chicago, the network begins to recognise historically marginalised groups predicated upon race. However, alone recognition does not ensure equality. It is important to consider the extent to which underrepresented groups can engage procedurally with the smart city.

### **7.3. Procedural sensor deserts**

A strength of the smart city is the availability of real-time data for decision-making. In many cases, however, the data are not openly available and therefore not scrutinised. Where data are open, it is likely that procedural inequality will arise as some groups will be less able than others to mobilise around it—including people with low internet use or literacy levels (Alexiou and Singleton, 2018), areas with high levels of political disengagement or transient populations and therefore limited agency for change (Burrell, 2016), or deprived populations with less time and resources.

As previously noted, a key strength of our case studies is that each commit to open data. Yet, the data is less likely to be accessed and acted upon by certain communities. Mapping of IUC in Newcastle illustrates substantial variation in internet access, reflecting the ability of different groups to utilise the data that sensor technologies produce. Areas classified as e-Withdrawn are less likely to benefit from coverage and less equipped to use the data to evidence change. This is likely to be the case in Chicago, where data is made available via a less user-friendly platform.

With issues of procedural and recognition inequality in mind, in the context of a shrinking state, smart cities often place the responsibility for engaging a diverse range of groups on citizen science initiatives. The Smart Chicago Collaborative has engaged with local communities across the city. However, the goal is to educate people rather than opening up decision-making about where to place sensors. The UO has developed an ambitious public participation mechanism via SensemyStreet, an online toolkit that enables local people to commission sensors, collecting evidence to inform change in their communities (SensemyStreet, 2020).

Yet, to some degree the onus is on individual communities to engage with these mechanisms, arguably attracting citizens that have a higher capacity to represent themselves. This is evidenced in Newcastle’s Clear Air consultations, to which relatively affluent postcodes contributed 75% of responses (Breathe, 2019). It could be argued that in areas less likely to participate, it is not worthwhile introducing infrastructures that will likely be redundant. However, this narrative feeds into a wider procedural injustice concerned with the way in which the introduction of infrastructures can de-responsibilise government (Vanolo, 2013). This is especially problematic when smart cities are left to fill the gap left by cuts to public services.

**8. CONCLUDING THOUGHTS**

With increasing volumes and ubiquity of data from new sensor technologies, areas that fall into the interstices of data collection are a key equity concern. In this paper we set out a framework for conceptualising sensor deserts—"actually existing” places and people on the ground, within cities, for whom sensor knowledge is not produced. We make visible potential inequalities related to being without sensor coverage. This is an explicitly spatial understanding of smart city inequality. People who live in sensor deserts lack information about their neighbourhood, meaning that there is less potential for evidencing urban challenges in—or conversely developing positive narratives about—their locale. More widely, a lack of sensor coverage signals a deprioritisation in terms of investment and is indicative of a lack of representation and visibility in decision-making about the (smart) city.

In practice, as shown by our two case studies, sensor coverage is complex, fragmented, and highly context specific, with evidence of successes and failures. Through balancing the need to integrate new sensors within the existing urban fabric, as well as engaging a diverse range of partners with often competing expectations, smart city agendas conflict with claims of social justice. There is evidence of sensor networks both challenging and reinforcing established geographies of inequality, whilst also generating new smart-specific spatial inequalities. These inequalities merit further systematic attention.

There are recognisable caveats in our conceptualisation of sensor deserts. As noted earlier in the paper, we take a default normative position that sensor coverage is generally positive. Our conceptualisation also holds under a negative connotation, however. In this case, for more surveillance-orientated sensors, for example, it simply becomes a privilege to inhabit a desert oasis of not counting: knowledge not produced equals official ignorance of behaviours that do not require a response. We are also unable to account for the politics of resistance to technologies. There is a wider debate to be had about implications for the responsibilisation of smart inequalities. Here, we analyse sensor deserts relative to the rest of the respective country rather than the city region. It was felt that a focus on the city region would risk deresponsibilising national government. This is especially pertinent in a context of spatially uneven reductions in local government budgets (Gray and Barford, 2018). There is also considerable scope to consider the manifestation of sensor deserts in contexts characterised by relatively informal, flexible and heterogeneous infrastructure networks, particularly in cities in the Global South (Chambers and Evans, 2019).

Methodologically, we assume sensor coverage based on whether a neighbourhood contains a sensor, or average distances from the nearest sensor. In analysing coverage, we do not consider sensor quality and favour proximity over diversity. Our analysis is shaped by the boundaries for which socio-economic datasets are produced. At times it is difficult to measure important aspects of inequality considering sensor deserts, particularly when avoiding modelled datasets that may themselves conceal deserts in coverage and understanding. Relatedly, datasets derived from the census, or similar, represent populations in a static way, spatially fixed in the home. We do not account for mobility and how people move in and out of coverage, with implications for commuting patterns, caring responsibilities, and poor health. There is further scope for understanding the local specificities of sensor deserts by deriving higher resolution and temporally dynamic sensor footprints (Xing et al. 2019).

Despite these caveats, our results have implications for best practice in the design of equitable sensor networks. The importance of considering equity in placement—or, who counts—from the outset is clear. Developing a network in a relatively ad-hoc fashion is likely to replicate and reinforce existing patterns of spatialized inequality, often leading to the placement of sensors in smart enclaves or where communities have the greatest voice and capacity to engage. The importance of a systematic approach to sensor placement is exemplified by the methodology produced by BreatheLondon (2019) which ensures sensor coverage in each Greater London borough, as well as placing a set number of sensors in each IMD decile. There is considerable strength in citizen science activities for engaging diverse communities in sensor placement, however, these participatory activities should also be accompanied by strategies for sensor placement that address systematic inequalities, without putting the onus on the individual to engage. With this in mind, sensor deserts should be on the agenda of all urban policymakers concerned with the evaluation, implementation and management of new smart technologies increasingly embedded within cities.

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1. *By mapping the data relative to the rest of the country we prioritise relative inequality within a country, rather than within the city region. In practice, this methodological decision made little difference to the results.* [↑](#footnote-ref-1)
2. *Census tracts rather than block groups (a higher resolution unit) were chosen due to the AoT network consisting of only 126 sensors.* [↑](#footnote-ref-2)
3. [↑](#footnote-ref-3)
4. *It is worth noting that the number of sensors in some categories (ie. beehives, water quality, water level) is relatively small. These results should be treated with caution, as the small sample makes trends in these variables difficult to interpret with confidence. There are positive relationships between the IMD classification and presence of an air quality (0.58), noise (0.72\*) and weather (0.75\*). A \* indicates significance based on a 95% confidence level.*  [↑](#footnote-ref-4)
5. *Contains National Statistics data (2017); Ofcom data (2016) and CDRC data (2017).* [↑](#footnote-ref-5)
6. *Note that some census tracts lie partially within or outside the City of Chicago boundary.*  [↑](#footnote-ref-6)