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Finding Common Ground for Citizen Empowerment in the Smart City

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Abstract

Corporate smart city initiatives are just one example of the contemporary culture of surveillance. They rely on extensive information gathering systems and Big Data analysis to predict citizen behaviour and optimise city services. In this paper we argue that many smart city and social media technologies result in a paradox whereby digital inclusion for the purposes of service provision also results in marginalisation and disempowerment of citizens. Drawing upon insights garnered from a digital inclusion workshop conducted in the Galapagos islands, we propose that critically and creatively unpacking the computational techniques embedded in data services is needed as a first step if we are to reimagine neganthropic, sustainable and empowering data services for inhabitants in diverse localities. We propose a therapeutic inspired by the concept of 'common ground' from communication theory. Common ground presupposes a symmetry of purpose, shared values and accessible participation processes. When common ground is deployed in the smart city context it prompts us to reimagine data services as an ongoing dialogue between peers, to rethink citizen participation in terms of capabilities and empowerment, and to focus on clear lines of accountability and equality of citizen outcomes.

Keywords: Surveillance, Data Capitalism, Optimisation, Prediction, Empowerment, Common Ground

Introduction

The[1][2] smart city as a concept emerged in marketing discourse in the 2000s and it is just the latest technological solution to promise better management and administration of cities (Zook 2017; Kitchin, Cardullo, and Di Feliciantonio 2019). Previously we had the 'wired city, the 'city of bits', the 'computable city' and the 'network city'. The emergence of smart city projects in Western countries is driven by a range of public research programmes, governments, market research consultancies and companies who are shaping a public expectation that contemporary digital technologies and artificial intelligence (AI) solutions will make public and private services more efficient and less costly (Kerr, Barry, and Kelleher 2020). The current iteration of smart city solutions requires both extensive datafication and dataveillance of city inhabitants and the integration of this data with other forms of data on the city. A range of predictive analytic techniques using the latest generation of AI, such as deep learning, are then applied to that data (Kelleher 2019). The results are used by human decision makers, or automated processes, to shape the delivery of services and infrastructures. Many smart city initiatives involve commercial companies partnering with cities, or taking over the running of city services, with little democratic oversight, accountability or scrutiny of the values or ethics of

[1] The author order is alphabetical by family name. Each author contributed equally.

[2] *To appear in Etica & Politica / Ethics & Politics¸ Guayaquil Archipelago: Epistemological Steps Towards a Real Smart City, Vol 22 (2), pgs. 33-61.* http://www2.units.it/etica/

the projects. For Zuboff (2019:376-397) this constitutes the development of a new apparatus of surveillance which she calls 'Big Other'.

The dominant smart city approaches to city administration has been extensively criticised from different disciplines, but governments, companies and researchers persist with smart city projects and initiatives. The term is now deployed to frame a wide variety of projects and technologies, but analysis of these projects has found that they often fail to empower all city inhabitants equally and may have detrimental social, political and environmental outcomes for some. What is evident is that we urgently need to bridge the gap between smart city discourses and the reality of everyday life in cities for millions of people. A majority of the world's population now lives in cities, and urbanisation is accelerating. Smart city discourses prioritise a top-down managerial and technocratic perspective of what a city is. However, cities are much more than machines to be managed and organised. Cities are complex social structures with dense populations which have their own rhythms (Lefebvre 2004). They have formal and informal markets, cultures, services and infrastructures. They are locations, places, and spaces. They have legal and illegal inhabitants. They are a 'theatre for social action', and a complex exorganism (Stiegler 2018). Many evolve organically and chaotically, and they are, as Lefebvre (1991) and later Massey (2013) noted, socially produced and relational. Cities have had distinct forms of governmentality over time, and values and politics can be designed into the fabric of cities as Winner (1980) noted. Yet while cities may be planned from above, they are experienced and lived from below, from the interactions of citizens, from the interplay of formal and informal structures and a myriad of practices. Cities may be spaces, but they are also places of dwelling and belonging (Sennett 2018).

Our approach to smart cities draws upon our respective backgrounds in communication studies, sociology and computer science. In this paper we conceptually explore the paradox that digital inclusion in smart city initiatives can lead to digital dis-empowerment for urban inhabitants and new forms of discrimination. We first situate our approach to contemporary smart city efforts within the broader 'cultures of surveillance' context enabled by commercial social media and the development of a pervasive platform logic to gather and exploit large volumes of data. We argue that at the core of post-industrial informational technologies are systems which by their design optimise and marginalise. Within information driven optimisation systems some of the key decisions are those pertaining to what should be optimised, the criterion used to define the optimal outcome, and what data is considered within the process. These subjective decisions often determine the outcome of the optimisation. Statements about the 'objectivity' of the information driven process that led to the decision conveniently ignore these human subjective stages in the process. Furthermore, in today's smart cities the deployment of contemporary AI techniques such as machine learning optimise and marginalise in new ways, both mathematically and socially, with a range of emergent outcomes for city inhabitants.

Many contemporary technical approaches to data gathering, analysis and exploitation are asymmetrical with regard to the knowledge and power of city inhabitants (and the observed) and are based on the assumption that human data is a freely available and a given resource. This has immense implications for the social, political and environmental sustainability of our cities. Digital inclusion in general, and in smart city initiatives more specifically, has a range of positive connotations and some positive outcomes. In this paper we critically and conceptually engage with the potentially negative implications of digital inclusion in smart cities for the everyday lives of city inhabitants and their rights. If we, as citizens, are included in the data flows of contemporary cities, but excluded from shaping, questioning or critiquing them, or if we have no understanding of how the production logics and techniques of data driven optimisation and prediction work, or if we have no say in the decisions controlling what is optimized and who it is optimised for, are we in fact losing control of our data, being disempowered and socially excluded? Attempts at public participation in the design of smart cities are often tokenistic and give little opportunity to co-produce the design of smart city projects. Or they only include privileged and already empowered inhabitants of the city. Digital inclusion in smart cities may even be detrimental to citizen rights. In the final sections we argue that we need to go beyond current solutions to user empowerment that focus on technical solutions, citizen centric design and ethics guidelines. We borrow from models of dialogue to propose that smart city initiatives that involve city inhabitants need to create a common ground and build capabilities attuned to the specifics of localities if they are to protect public values and maintain the trust of urban inhabitants and city administrators. Only then can we reimagine a more symmetrical economy of contribution and greater citizen empowerment in real city contexts.

Smart Cities in a Culture of Surveillance

Smart cities are not a unique socio-technical infrastructure. Smart cities are just one part of a wider culture of surveillance across contemporary economies and everyday life. What some call surveillance capitalism (Zuboff 2015, 2019), David Lyon (2018) calls a 'culture of surveillance' that brings together the activities of private corporations and states with the everyday activities of urban inhabitants as we hail taxis and buy food using apps, as we search for accommodation online and rate our lecturers. The growth of a culture of surveillance and smart cities is in part due to the rapid growth in computing power and the widescale diffusion of fast internet and networked or smart screens, sensing devices and objects in many countries. With the diffusion in many countries of commercial but free to download social media over the past decade, and the introduction of AI systems by state and city governments to better administer transport, policing and public services, we are all participating in a shared culture of surveillance. In this culture of surveillance power is asymmetrical and in many instances the gathering and use of data is not transparent to the citizen. We may freely use, and feel digitally included, in the digital economy – especially by the cute representations of interaction and networking that are presented back to us as icons and numbers. At the same time, we may be completely unaware of the deeper levels of datafication, extraction and prediction that are being conducted using our data and its implications for our autonomy and freedom as consumers and citizens. The uses to which our data is put may only become apparent when we are refused the right to board an aircraft because of our security profile and we fail to be shortlisted for a job because our address, travel history or gender weigh too heavily against us. Or ironically, the lack of a data profile may equally be used as a reason to deny one the right to move or to participate in the city.

Taking a culture of surveillance approach, we can see that the city is not just created by top down technological systems, but it is also created by a range of bottom up practices of inhabitants, including their social media use (in the broadest sense). Cities with informal settlements, with non-marketized forms of work, and with a variety of local cultures, pose immense problems for a data driven system of algorithmic control intent on capturing all available data. The informal flows of urban inhabitants are however captured by commercial social media services and shared across smart city and social media infrastructures. Individuals who participate in informal and non-market practices may be politically excluded, but digitally included in commodified data flows. Citizens who are formally included in the marketized institutions of their cities and represented in its public and private digital streams may be digitally included but their agency may be reduced to data provider, 'user' of privatised data flows and target for advertising. Just as earlier conceptualisations of knowledge in the knowledge economy narrowed our understandings of knowledge to that which could be codified and traded (Kerr and Ó'Riain 2009), similarly current conceptualisations of data and AI are narrowing what we conceptualise as data to that which can be digitised, analysed computationally and exploited economically. Data about a city and its inhabitants exists in many forms – from stories and images, to sounds and memories. Indeed, Fitzpatrick (2020) argues that the data city might be a better term. A data city explicitly acknowledges that the data representing a city should, for example, include historical records (e.g., early census data) and fictional representations (such as Joyce's portrayal of Dublin in Ulysses). Currently, smart city technologies reduce cities to uniform spaces without histories or variation. Smart cities are not designed to capture this variety of data, and they cannot see it. Smart cities are designed to 'flatten out' knowledge to what can be datafied. Smart cities don't count or can't count the social life of cities and civic life in the city. Further, smart city solution providers rarely engage with discussions about environmental sustainability and the Anthropocene beyond superficial platitudes. There is little assessment of the impact of smart city initiatives and their data farms on land, energy and water use.

Most commercial social media share a common production logic with smart city projects. Indeed, often the services are offered by the same companies. A production logic is a relatively stable set of institutional forms and relationships created by the commodification and industrialisation of culture (Miège 1987, 2011). The concept developed in relation to the traditional cultural industries where three dominant production logics were identified – the editorial, the publishing and the flow logic. The approach has been adapted to the contemporary cultural and creative industries (Kerr 2017). The smart city production logic most closely adheres to a commercial data platform logic. This logic has become more evident since the 2008 financial crash and the necessity in public administration to focus on efficiency and cost savings. Indeed, some argue that the 2008 crisis necessitated a shift in the narratives of smart cities from an emphasis on sustainability and climate change to a narrative focussed on entrepreneurship and platformisation (Baykurt and Raetzsch 2020). This logic produces data markets that are brokered by private corporations, turn public servants and public institutions into project managers/commissioners, circulates freely given and citizen created content, and datafies its citizens by extracting digital forms of data, analysing them and creating economic value out of them. Smart city technologies mobilise sensors and other technologies in the city to gather live data about, and from, inhabitants and visitors to the city and this data is then mined using AI to generate derived data about an individual so as to provide actionable insights for a range of third parties that enable them to optimize processes for their preferred outcomes. These procedures, processes and their outcomes are largely invisible to city inhabitants, and indeed they may be opaque to city administrators also. They are also anathema to those who conceptualise the city as a public space that should be shaped according to the needs of all inhabitants.

The corporate smart city discourse is based on the datafication of social behaviour and the presumption that all meaningful activity can be sensed, measured and used to eradicate inefficiencies within workflows of a city, conceptualised as a machine (Mattern 2013). It is ultimately another technique of societal control. The datafication and quantification of social behaviour is not new and scholars like Oscar Gandy (2016, 1996) have long analysed the use of decision support systems by commercial companies as 'discriminatory technology in the panoptic sort' (2016:vii). His 2016 book points to the widespread use of 'predictive intelligence' and warns of the social costs for citizens of the widespread use of discriminatory technologies to guide business decisions. His analysis draws upon the use of prediction techniques in finance, criminal justice and public policy formation in the United States. The detailed exploration of the use and potential outcomes of these technologies and their models is continued by Donald MacKenzie (2008) in relation to financial markets, Joe Turow (2012) in his analysis of the advertising industry and Dencik et al. (2017) in relation to policing. Mansell (2004, 2012), Pierson (2012), van Dijck (2014), and Zuboff (2019) have drawn our attention to the negative implications of data extraction by social media for user empowerment, and Kelleher and Tierney (2018) highlight how the turn to data science can undermine privacy, amplify profiling, reinforce discrimination, and result in more technocratic societies.

Zuboff (2019) explores in detail the prediction imperative and its role in the logic of accumulation at companies like Google and Facebook. Zuboff details how surplus behavioural data can be analysed using 'machine intelligence' (2019:96) to create value through selling this data to advertisers and others. She points to how contemporary commercial platform logics in search, social media and smart city technologies aim to capture more and more of everyday life, including locational data. This phase of surveillance capitalism is not only about mapping and routes, but about routing (2019:152). The focus of many of these techniques is not just about showing us relevant advertising and information, it is also about influencing user behaviour in 'real spaces in everyday life'. Further, they reduce meaningful social activities to that which can be digitised, captured and exploited economically. They reduce city administration to the control and modification of data flows and city inhabitants to their data traces. For van Dijck (2014) the normalisation of datafication and dataveillance across society has led to the emergence of a new paradigm or belief in 'dataism' – which assumes not just a belief in the objectivity of data, but also requires trust in the institutions and wider ecosystem that use it.

The smart city agenda must be conceptualised within this broader turn to dataveillance, prediction and dataism. It has justifiably received a lot of criticism. It has been criticized for its narrow conceptualization of 'the city' and attempts to reduce the complexity and uncertainty of urban life to a limited type of data. It has been criticised as providing technically determined solutions to social problems (Morozov 2013) and technocratic and undemocratic forms of city governance. While examples of smart cities being designed on green field sites exist – notably Masdar in the UAE and Songdo in South Korea – most 'actually existing' smart city initiatives are grafted onto existing cities and involve complex public/private partnerships or contracts (Shelton, Zook, and Wiig 2014). Their diffusion has been facilitated by political choices at city, state and regional levels and targeted research and innovation investment. Recent research has identified different approaches to smart cities in North American and Europe, with the latter adopting a more 'living labs' approach (Baykurt and Raetzsch 2020). Others point to different impacts of big data practices in postcolonial contexts and the need to attend to the differential development of citizen rights, power and marginalisation in different contexts (Ruppert and Isin 2019). In this context studies that highlight the ways in which citizens can re-appropriate commercial smart city solutions as new forms of civic infrastructure are welcome (Perng and Maalsen 2020). Some research projects now explicitly try to reimagine city data gathering platforms in terms of public interest needs and civic infrastructures and others explore and build co-operative platforms[3]. These types of projects are however rare. More frequently we see that cities are being redesigned as 'entrepreneurial' cities which brand and develop their services to promote business innovation and consumption (Lawton 2009), rather than deliver

[3] See for examples the European DECODE project at https://decodeproject.eu/ and the international projects at https://platform.coop/

public spaces and services for all inhabitants (O'Keeffe 2014; Lawton 2009; O'Keeffe and Kerr 2015).

Legislative and activist attention on datafication has largely focussed on the privacy implications of mainstreaming dataveillance and cultures of surveillance. In Europe data protection legislation is beginning to regulate the ways in which smart cities can work. The European General Data Protection Regulation (GDPR) was introduced in 2018 and is one of the first major legislative attempts to regulate data gathering and to protect user privacy, particularly in relation to personal data. This regulation supplements and strengthens existing policies such as the Data Privacy Shield which attempted to provide a legal basis for the sharing of data between companies in the US and Europe (O'Rourke and Kerr 2017). GDPR and related policies aim to make data gathering and use more transparent and those who are gathering it more accountable. However, a useful starting point in this aim of greater transparency in contemporary data economies is to understand how 'smartness' in smart cities works. Smartness in smart cities relies not just on data gathering and extraction, but also on applying prediction and optimisation techniques to that data to generate 'actionable insights' that inform decisions and shape outcomes. In what follows we introduce the concepts of digital footprints and explore how predictive modelling in AI operates (Kelleher and Tierney 2018).

Digital Footprints and Predictive Modelling in AI

The proliferation of sensors in modern urban environments and the diffusion of smart phones and social media use means that it has never been easier to collect data on citizens. The amount of data that is currently captured about citizens as they move through an urban environment is much higher than most inhabitants are aware of, and can be done through a variety of channels, including face recognition applied to on-street or in-door video surveillance, credit card purchases and ATM withdrawals, loyalty schemes at supermarkets, and the tracking of mobile phone calls. In 2009 the Dutch Data Protection Authority estimated that the average Dutch citizen was recorded in 250 to 500 databases, and this figure could rise to 1,000 databases for some citizens (Koops 2011). Haggerty and Ericson (2000:613) introduce the concept of the 'data double' building upon the work of Mark Poster (1990:97), to conceptualise an abstract multiplication or an additional self that circulates in centres of calculation. Others call it our data shadow, and they argue that "what we are witnessing at this point in time is the triumph of representation over being" (Critical Art Ensemble, 1995, cited in Kitchin 2014:177)[4].

We introduce the term *digital footprint* to describe all the data trails that a person leaves as they move through an environment. These data trails can be captured under two different conditions: 1) a person may choose to share data about themselves, or 2), the data may be collected without the awareness and/or consent of the person. To distinguish these two conditions of data capture, the term data footprint is used to describe data that is collected with the awareness of the individual, and the concept of the data shadow is narrowed from its previous uses, to describe data that is captured about an individual without their awareness. Both are subsets of one's digital footprint, see Figure 1.

[4] See http://critical-art.net/

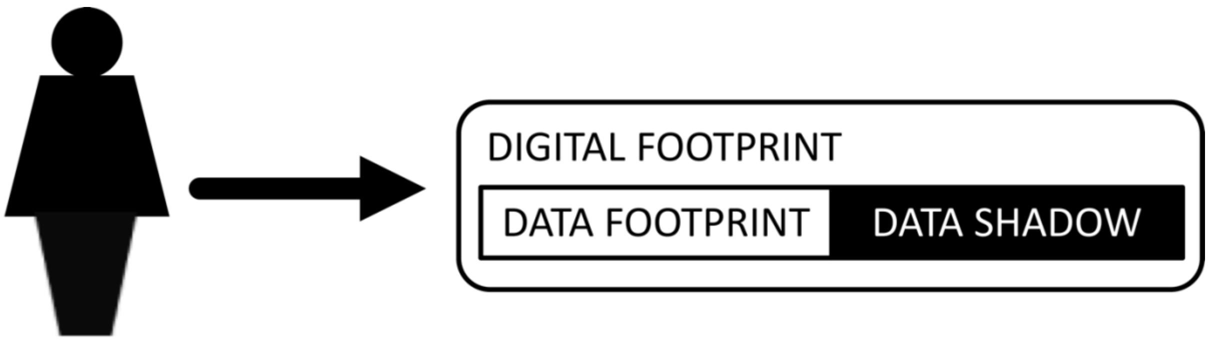


Figure 1 The Datafied Citizen

The collection of data pertaining to an individual without their awareness is problematic, but it occurs constantly in public smart city projects. However, even data that is collected with the consent of an individual can be harmful to them in ways that they are not aware off and may be used, reshared, or repurposed in ways that they did not expect, or indeed were not aware were possible. The fact that multiple data sources may be merged without an individual's knowledge means that different pieces of data that an individual consented to share in separate and distinct contexts may later be integrated into the digital footprint of the individual; and, these out-of-context data linkages, combined with the power of modern predictive modelling systems, means that accurate and inaccurate inferences in relation to sensitive personal characteristics (such as their sexual orientation, political and religious views, and their use of addictive substances) may be inferred from data that might appear unrelated. Indeed, it is just this type of inferential analysis of data that modern AI technologies enable.

The AI methods used to analyse contemporary forms of big data are commonly termed: Machine Learning, Deep Learning and Predictive Analytics, (Kelleher 2019; Kelleher and Tierney 2018). Broadly speaking modern AI can be understood as a set of technologies that are designed to support data-driven decision making. The core idea being that the AI system can 'crunch the numbers' to find some insight into a problem that informs the outcome of the decision. The current wave of innovation in AI is primarily driven by machine learning. Machine learning is the subfield of AI that designs and evaluates algorithms that can learn from data. Within a datafied system, be it a smart city or some other system, all entities (people, objects, documents, locations, events, processes, and so on) are represented by vectors of features, where each feature records a measurement of a single aspect of the entity. In this context, machine learning from data involves selecting a computational model based on patterns of correspondence between features in a dataset so that the model can accurately map from a set of known input features to a value for an output feature. The computer model predicts the unknown output, and the computer model encodes the rules (extracted from the data by the machine learning algorithm) mapping from the inputs to the output. This task of mapping from a set of known inputs to the unknown output value is known as prediction, hence the computational model that encodes the mapping is known as a prediction model.

To provide a concrete example of how predictive AI works imagine a citizen in a smart city applies for rent support. As is the case with all datafied entities the digital footprint of this citizen will be encoded as a vector of features. Now imagine, that one element (i.e., feature) of this citizen's digital footprint is missing a value and this missing value would be useful in informing the rent support decision. There are many reasons why the value for a target feature may be missing from an individual's digital footprint. Indeed, the citizen may have actively chosen to keep it private. Figure 2 illustrates this situation and uses the '?' to indicate a missing value in the digital footprint. We use the term *target feature* to denote the feature in the dataset for which the value is missing. The goal of predictive AI is to predict the missing value of the target feature.

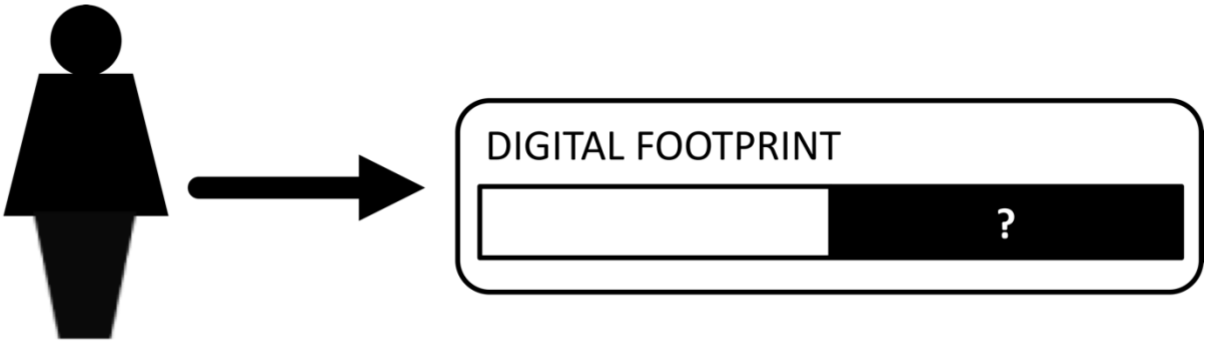


Figure 2 The Datafied Citizen with Data Missing from their Digital Footprint

This missing data value can be predicted (or inferred or estimated) using a prediction model. Figure 3 illustrates the data capture, analysis and decision process enabled by AI predictive models. The process begins by capturing data relating to other citizens in the city in which the digital footprint of each citizen included in the dataset records a measurement corresponding to the missing data for the citizen in Figure 2 (i.e., each of the digital footprints in the dataset records a value for the target feature for the citizen the digital footprint describes). Once the dataset has been created the data analysis process begins. There are two phases to the data analysis process, training and prediction (also known as *inference*). In the training phase a machine learning algorithm processes the dataset and selects the prediction model that most accurately maps from a set of known inputs (the values for the features in a digital footprint that are not the target feature) to a value for the target feature (i.e., the prediction model's output). Once the prediction model has been selected the second phase of data analysis (the prediction or inference phase) begins. In this phase the incomplete digital footprint for the citizen is inputted - into the prediction model and the model generates an estimate of the value for the target feature. This predicted output is then used to inform the final decision of whether to grant rental support or not.

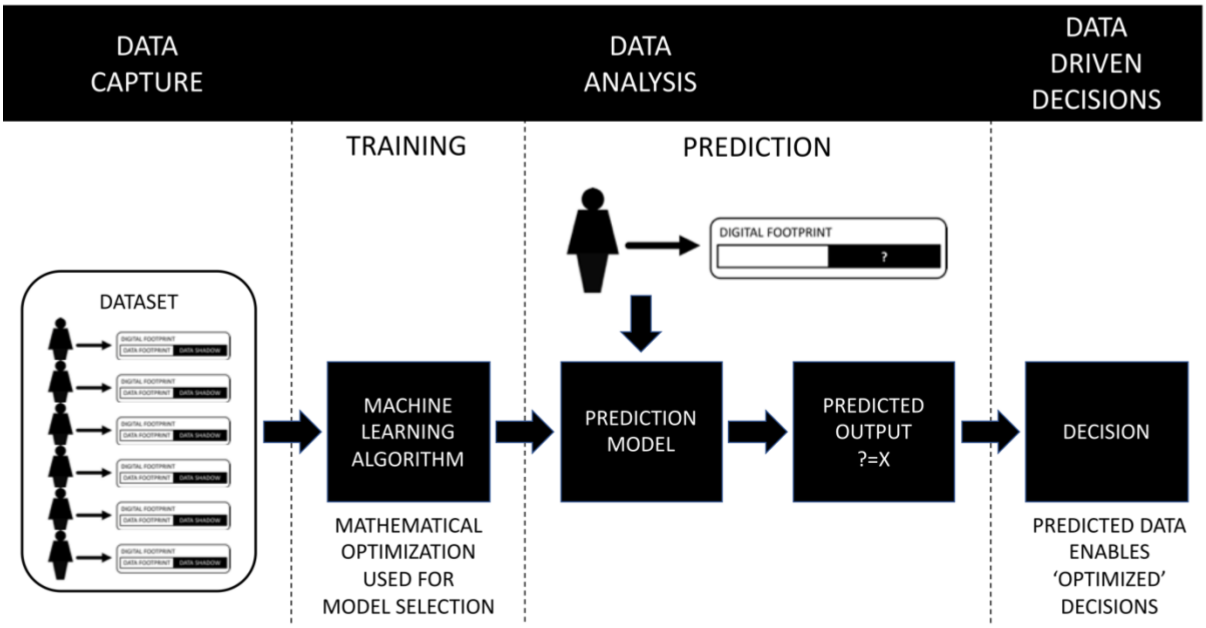


Figure 3 The data capture, analysis and decision cycle enabled by predictive AI

The process of predicting an unknown output value based on a set of known inputs links to decision making in that the predicted value is used to inform or drive the decision. In the above example we have focused on predictions pertaining to individual citizens; however, the problems to which prediction techniques are applied are multiple: for example, a predictive model could be used to map from a set of inputs describing an email to an output that identifies whether the email is spam or not, from a set of features describing a loan application to an output determining whether the loan should be granted or not, from an image of a street to an output describing whether an 'individual of interest' is present in the image, from a set of features describing a location in a city at a particular time to whether a police patrol should be deployed there in the next hour, and so on. Furthermore, in many of these cases the prediction made by a model is not used by a human decision maker but rather triggers automated algorithmic governance. In scenarios where decisions are automated the prediction model is given an agency that directly impacts outcomes for individuals within a city. Indeed, even where a human decision maker is in the decision loop, prediction models still retain agency in that they often indirectly affect decisions and outcomes. In this new AI predictive reality, prediction is part of a new 'animism' (Hildebrandt 2015) as objects become more animated and active in our everyday lives.

One application of predictive analytics for which a significant amount of research has been done is to create predictive models that forecast individual trajectories through a city. The motivations for this research can range from optimizing traffic managements, to urban planning, and location-based advertising (Kulkarni et al. 2019). The accuracy of predictive models on this task is very high. For example, Song et al. (2010) found a potential predictability of 93% across a dataset of human mobility of 50,000 individuals, and more recently Kulkarni et al. (2019) showed that by extending the information used by the predictive models the upper-bound on the accuracy of these models can be further increased. The results of this research indicate that human mobility behaviour is highly predictive, irrespective of variations between individuals in terms of the distance they cover on a regular basis. A positive reading of the regularity and predictability of human mobility behaviour is that smart city technology can be successfully applied to a range of applications based on human mobility, e.g. traffic management, etc. However, the negative implication is that unless the appropriate safeguards in relation to data collection and data reuse are in place then individual privacy and freedoms are seriously diminished. The fact that modern data driven models can be used to infer an individual's characteristics and to predict their location means that the infrastructure of a smart city can readily be repurposed to continuously surveil citizens.

The development of a culture of surveillance with both commercial smart city technologies and broader social media technologies collecting data, both with and without our awareness, and a range of predictive technologies attempting to control and cajole social behaviour has turned the contemporary city into a generalised panopticon. The panopticon is a building developed by Jeremy Bentham in the 18th century that was intended for use in institutions, such as prisons or psychiatric hospitals. The building was designed so that the staff could observe the inmates without the inmate's knowledge, and so the inmates were forced to act as though they were always being watched. As Foucault (1977) notes, the panopticon is "a mechanism of power reduced to its ideal form." It is one of the most pervasive metaphors for the regulation of bodies by technologies and it has been applied to a range of technologies. Surveillance in the panopticon was based on looking and it was used to monitor and control people for specific purposes.

Some have argued that the panopticon and surveillance as metaphors and concepts are insufficient to capture the ways in which contemporary big data is now being repurposed by corporations, states and citizens to surveil everyone everywhere (Andrejevic 2004; Braman 2006). We are post-panoptical for Lyon (2018:34) while others still wish to keep the critical insights of the original Foucauldian critique (Simon 2005). Indeed, even if we hold onto the critique, it might be appropriate to think about the convergence of discreet surveillance systems into broader 'surveillant assemblages' and to approach the culture of surveillance as one in which all types of data are gathered all the time for unspecified purposes (Ericson and Haggerty 2006; Haggerty and Ericson 2000; Braman 2006; Van Dijck 2014). As Lyons (2018) notes, while the surveillance State and surveillance capitalism suggest surveillance is done to us, surveillance culture is even broader and points to the deep entanglement of surveillance in all aspects of social life. Smart city systems cannot be divorced from everyday data driven consumer systems such as social media or supermarket reward systems. Even when our data is missing from the specific informational system, automated processes can be used to predict and infer our features with a high degree of accuracy. The focus of any therapeutics therefore needs to be not only on consent, or awareness, but also on the ways in which these systems optimise and marginalise certain behaviours and outcomes.

Smart Cities as Socio-Technical Systems of Optimisation and Marginalisation

Sociologists of technology have long argued that technologies are never value free (Feenberg 2012; Wajcman 2004; Winner 1980). Thus, it is important to investigate the choices and values that are coded into contemporary datafication systems and optimisation techniques. In this section we aim to unbox some of the AI technologies and methods within Zubuff's prediction imperative (2019) and debunk the notion that such systems are value free. The commercial smart city discourse foregrounds the computational quantification and algorithmic governance of a city to more efficiently manage infrastructures and services and reduce costs (Greenfield 2013). The technocratic language often positions city administrations as inefficient, private enterprise as the deliverer of innovative solutions, and city inhabitants as passive providers of data and receivers of services (Coletta and Kitchin 2017; Coletta, Heaphy, and Kitchin 2019). They portray smart city technologies as data driven algorithmic systems for decision making that are objective and neutral, apolitical and value free, following the more general turn to 'dataism' (van Dijck, 2014). Algorithmically driven optimisation processes rely on a range of decisions including accessing a pre-existing data set, choosing between different abstract models, and the creation of model selection criteria. In other words, these algorithmic processes are based on a range of choices and decisions made by humans, and the resulting socio-technical systems can introduce, emphasise or amplify digital and social inequalities.

Managing a city involves a multi-level set of strategic and practical decisions, for example on the allocation of services and resources, on the routing of public transport, and the funding of art and cultural initiatives. In its most general sense, optimisation of decision making in a city involves gathering evidence to inform policy development and the selection of an approach from among a set of alternatives which maximises (or optimizes) for some predefined criterion defined usually in relation to the public interest and quality of life in the city. Similarly, in a data driven optimised decision-making process, choices must be made as to the design and selection of the decision criterion, and how the assessment criterion is applied to the considered alternatives (Kitchin 2014b; Gandy 1996, 2016; Kitchin 2014a). It is also crucial to know who chooses, which alternatives are considered, and what criteria or values inform the choice. Each of these decisions feed into the determination of the final decision, and each of these decisions is open to subjectivity and bias. Furthermore, any decision process, be it framed as optimisation or not, necessarily involves the selection of one outcome and the rejection of alternatives.

The promise of current smart city technologies is that big data and AI systems will enable the optimal running of the city in an efficient manner. Indeed, as shown in Figure 3 the process of optimisation (or selection to maximize a criterion) is also at the core of modern AI and machine learning. However, it is important to recognise that the appeal to 'smart' data driven predictive technologies does not remove the problem of bias within the decision-making process, nor the resulting marginalisation of those who are not optimised for. The machine learning task of learning from data involves an algorithmic process that selects a predictive model from a set of alternative models based on which candidate model best fulfils the predefined criterion. There are many different machine learning algorithms, for example, backpropagation, stochastic gradient descent, and linear programming. However, as Kelleher (2019) sets out all of these machine learning algorithms requires the following inputs (1) a dataset of examples, (2) a set of candidate models that will be considered for selection, (3) a model selection criterion, also known as an objective function or a fitness function; and, given these inputs all of these algorithms search through the set of candidate models to find the model that best fulfils the objective function with respect to the dataset. In effect, all these algorithms are optimisation processes, which differ in the ways that they define the set of candidate models and how they organise the search through the candidate prediction models.

Figure 3 illustrated how mathematical optimisation is a key step within the data capture, data analysis and data driven 'optimised' decision process at the heart of modern AI and smart city technology. Within this figure the analysis step frequently involves using machine learning to induce a predictive model from the data, and then using the predictions of the model to inform/drive 'optimised' decision making. Importantly, for this discussion, although the term 'optimisation' can at a surface level appear to be a positive outcome, any optimisation is a trade-off. Optimising for one outcome necessarily means marginalising other possibilities. It is impossible for an information system to optimize for all outcomes at the same time. This is a crucial factor to consider when such systems are introduced into our cities and deployed in relation to public services. Just as with the optimisation of a social system, the choice of one alternative decision-making process (in this case, prediction model) necessarily involves the marginalization/discarding of alternative decision models. Although it may not appear that the preferencing of one computational model over another should be of serious concern to us from a smart city perspective this is not the case. In the modern smart city context these computational models have impact in the world and their decisions affect real lives, and so the selection of a particular predictive model through a computational process of optimisation of an objective function viz-a-vie a dataset is directly related to the marginalisation of groups and individuals who would have received better outcomes if a different model had been selected for deployment.

What is more, the computational process of optimisation is as open to subjective bias as any social system of optimisation. The same questions that are rightly asked in the social context with respect to who chooses what outcomes we should optimise for, what alterative solutions will be considered and what criterion should be used to guide the choice, are also directly relevant in the algorithmic optimisation of decision making that affect our lives. Indeed, further questions are also necessary, such as which data is used or not used and why. Emerging research has found that the application of AI systems by city administrations and third parties to public services such as housing, health and policing, can result in very real forms of discrimination and inequality for urban inhabitants, as Virginia Eubanks (2018) has documented in the United States and Dencik et al. (2017) in the UK. Thus, data driven algorithmic systems can result in a range of social harms and biases.

Some research is now attempting to produce technical solutions to address discrimination, bias and marginalisation in AI systems. Gürses et al. (2018) note that an objective function may not consider the distribution of a system's errors toward minority groups, or the fact that the objective function may not consider how a system's performance will vary when it is deployed into different contexts to the one the data was sampled from. Emerging technical solutions include fairness by design frameworks, pareto optimal outcomes and explainability in AI. Others propose non-technical solutions to the potential harms of AI systems including trusted third parties, collaborative online platforms, various forms of technology impact assessments (Nemitz 2018; Veale and Binns 2017) and a range of highlevel ethical guidelines have emerged. All these solutions provide some legal cover but leave many things unexplained. They also fail to question the nature of optimisation at the heart of algorithmic design making, and the continued unfettered deployment of big data surveillance regimes in social and public contexts.

From Digital Inclusion to Social Inclusion in the Smart City

In the contemporary city data is being gathered, aggregated, analysed and used to predict citizen behaviour constantly. Given the pervasiveness of data sharing across information systems, it is almost impossible to be 'off grid' or digitally excluded, even if one is a non-user of some of these systems. It is instructive to revisit national information and knowledge society policies from the 1990s which focussed heavily on overcoming the digital divide through enabling digital access and internet skills as a progressive form of social and political inclusion in society. Studies of technology use quickly found that digital access and use were no guarantee of social inclusion or equality of outcomes (Mansell 2017). Even when **access** to digital technologies becomes more widely available in many countries and operational internet skills grew, the capacity of people to search for, understand and deploy information remained a challenge. Much of this literature now distinguishes between **levels of digital divides** including a first level of access, a second level of internet skills and use, and a third level focused on outcomes of use (Scheerder, van Deursen, and van Dijk 2017). Digital inequalities in internet use persist in societies that are heavily networked, and they have been shown to be related to a range of factors including socioeconomic status and education (Hargittai, Piper, and Morris 2019). Non-use and usage barriers persist due to variations in network diffusion and local public and commercial strategies and priorities. At the same time, we may need to rethink the concept of the digital divide entirely in societies with extensive data gathering infrastructures.

Most top down smart city initiatives and bottom up commercial social media use are examples of first level **digital inclusion and of data capitalism**, and we need to be careful not to conflate that with **individual or social empowerment or with social inclusion**. Digital inclusion is not synonymous with empowerment or social inclusion. Most analysis speaks little of the negative and positive implications of digital exclusion for non-users. We must also think about the implications of digital inclusion in the culture of surveillance given the partiality of the vision or intelligence provided by the datafication of social life and the intensification of the prediction imperative (Pierson, Mante-Meijer, and Loos 2011; Pierson 2012). In most cities and countries there are **islands of digital exclusion and inclusion** and differential impacts and outcomes of digital access. Existing systems of city governance and oversight are no guarantee that equitable social outcomes and accountability will be achieved through digital inclusion.

Our fieldtrip to San Cristobál on the Galápagos islands challenged two important presumptions that we had of the islands prior to arrival. First, our knowledge of the Galápagos islands is filtered through the writings and teachings of Charles Darwin on the local natural environment and the primacy of his view of the islands overshadows and excludes the voices of the inhabitants. It is a partial view at best of the islands. A co-curated exhibition of work by local artists about the islands challenged his voice in many ways. A march by local teenagers against a plan to land American military planes on the islands provided another bottom up perspective. Second, despite their location on a remote island off Latin America and mainland Ecuador the islanders, did not feel digitally excluded from contemporary digital networks or cultures. According to the island museum, they have long had local radio stations and local television stations. This highlights that they have some control over traditional media representations of themselves.

Figure 4: Public encounters with the Arts exhibition, San Cristóbal, Galápagos Event 25-26 July, 2019.

In July 2019 we organised a public engagement workshop in the local cultural centre in Puerto Baquerizo Moreno, on San Cristóbal island in the Galápagos islands. Following some short presentations on the topic of the Anthropocene, data capitalism and digital inclusion and exclusion we broke attendees into small groups. We used a diagram that placed digital inclusion and exclusion and data capitalism and data sovereignty along two axes to help structure discussions (see figure 5).

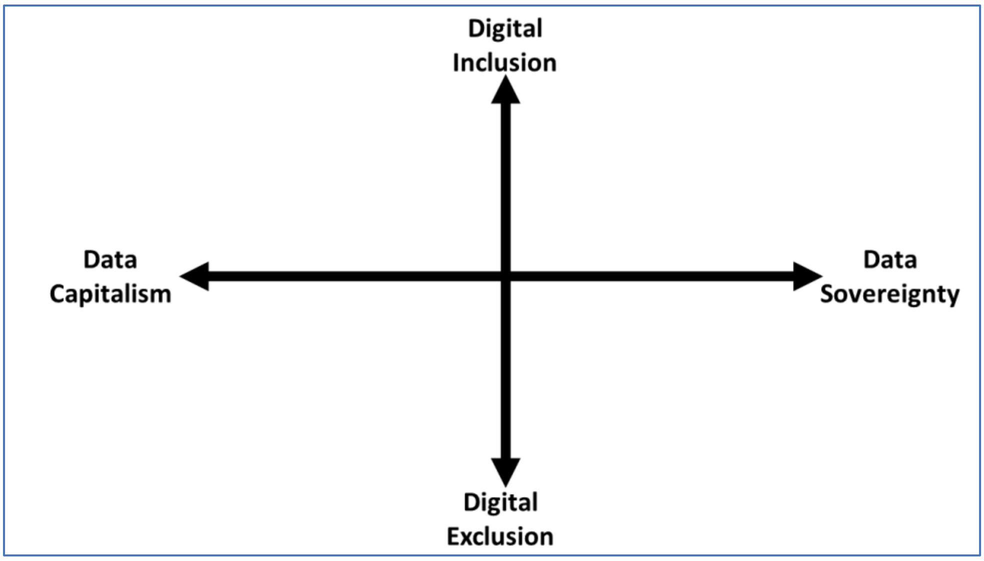
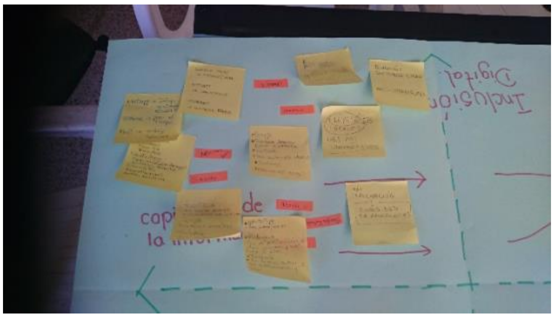
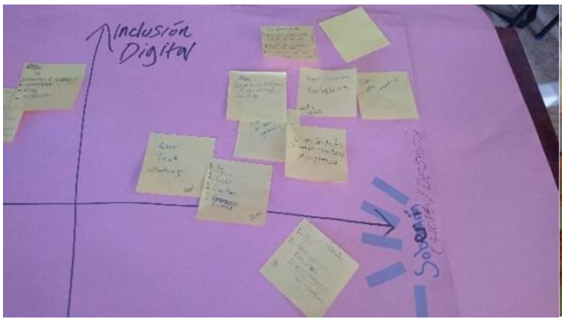


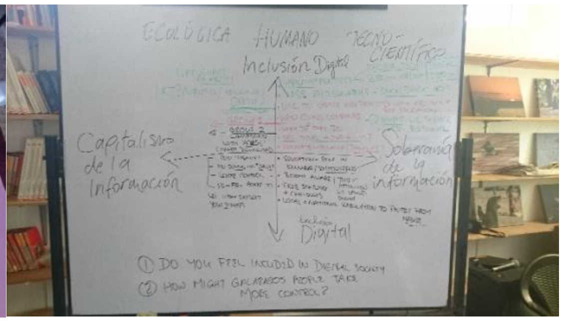
Figure 5: A diagram to structure discussions.

We began the discussion by asking attendees from the islands about their perceptions and experience of digital inclusion and exclusion. Many felt digitally included because they had access and used North American social media and internet services. They populated the top left of our diagrams with multiple examples of internet services we are familiar with in Western Europe including Google, Facebook and WhatsApp (see figures 6 and 7). Their internet access and speed were often poor, and they relied heavily upon commercial locations such as cafes and tourist offices to access it, but they did not feel digitally excluded. We then asked participants to think about how the economics of these services worked and how commercial data capitalism operated. Many were unaware of the production logics underpinning free data services and the differences between data footprints and data shadows. Most were unaware of alternative services to Google and Facebook including open source and co-operative platforms. They had not thought about what kinds of alternative digital services might be developed on, and for, the inhabitants of the islands. The complexity of digital inclusion raised important questions on an individual and a collective level. Participants were encouraged to move their 'post-its' around the board as our discussions developed. We discussed how services might move from the top left of the quadrant to the top or bottom right – or how a balance might be achieved (see figures 8 and 9).



Figures 6 & 7 – Discussion 1 on Digital Inclusion and Exclusion on the islands. Top left square heavily populated with examples.





Figures 8 & 9 - Discussion 2 on Data Capitalism and Data Sovereignty and summary notes of group discussions. Some examples starting to populate the top right quadrant.

Our workshop discussions underline the complexities of digital access and participation in the contemporary digital economy. We need to question both the marketing of digital media companies and classical liberal approaches to freedom and agency which elevate and conflate digital user agency and use of services with user choice and freedom. In the marketing and classic approaches digital user agency is often conceptualised, or framed, as freedom **from** the powers of the state and freedom to say and do as one chooses. Such an approach to user agency is evident in early North American cyber-libertarianism and what has been called the California ideology (Turner 2009; Barbrook and Cameron 1995; Turner 2010). It is also part of the market led and the market/state led imaginaries and policies informing the development of the digital economy and digital markets (Mansell 2012).

If however we seek to engage with alternative imaginaries, values and conceptualisations that go beyond first level or instrumentalised digital inclusion, we need to shift the focus away from a negative freedom from, and towards more positive **freedoms to** behave within social and cultural contexts according to wider social norms, rights, duties and responsibilities. While such freedoms are always conditioned by the context in which they exist, a focus on freedoms in context, or localities, takes us beyond rhetorical forms of agency and moves us more towards deeper forms of human autonomy and the social good. If we are concerned with the relationship between digital inclusion and social inclusion, and more pertinently their relationship to equality and outcomes, then we need to look beyond individualised approaches to digital inclusion and towards structures that facilitate collective empowerment.

These types of empowering structures are not evident in current approaches to public engagement and citizen participation in smart city projects. Current citizen-centric and citizen engagement smart city initiatives organised by both public and private groups are driven by the need for political legitimacy of projects, the pressure to justify public investment and a desire to demonstrate research impact. Cardullo and Kitchin (2019) provide a scaffold of citizen participation in smart city initiatives. In their examination of smart city projects in Dublin, Ireland they found that citizens most often “occupy non-participatory, consumer or tokenistic positions and are framed within political discourses of stewardship, technocracy, paternalism and the market (2019:813-830)”. The most empowering examples they provide include civic hacking and living labs. However, while hackathons, and living labs generally result in deeper levels of participant engagement, such initiatives are relatively exclusive (especially where programming skills are involved) and not available to all (Kerr 2020; Barry, Kerr, and Grehan 2019). Running public engagement hackathons at weekends and in the evenings presupposes people do not have caring or other responsibilities, and most of these types of events rely on people bringing their own computers. Studies of citizen led hacking and coding initiatives found that they were fraught with frictions and contradictions (Perng, Kitchin, and MacDonncha

2018). Meanwhile, commercial social media provides a widely inclusive, but shallow form of digital inclusion, again providing a consumer led perspective on agency. Explicit attempts to engage citizens in co-designing or rethinking smart city initiatives need to be evaluated for their both their inclusiveness and their outcomes.

These findings are not surprising. Feminist scholars have found that gender 'empowerment initiatives' often fail to address gender inequality because they focus only on individual behaviour, and not on changing the structural conditions or cultures within which this behaviour occurs. For example, a critique of gender empowerment initiatives found that empowerment initiatives were often individualised, required those who were already marginalised or excluded to do the work, and often left the structures and cultures unchanged. Empowerment initiatives to date also presuppose individual freedom, resources and capabilities to act – a feature that seems to display a distinct Western liberal democratic bias, as Sharma (2020) cogently argues. For digital inclusion initiatives to move beyond performance and rhetoric, they must engage with local and global structures of power and issues of resources. The move in smart city projects towards citizen centric design and engagement remains largely performative, and there are few examples to date that focus on inclusiveness and social outcomes. Most focus on a limited set of needs and are shaped by interests far removed from the majority of inhabitants. How can we bring a focus on social inclusion and equality of social outcomes into our discussions?

Finding Common ground to Govern the Smart City

Our analysis so far reveals four important aspects of data driven decision making in the smart city and surveillance cultures more generally:

(a) Human behaviour is highly predictable, and even if your data is missing in a system it can be inferred.
(b) Current data driven infrastructures amplify the ability of authorities and companies to surveil and control citizens without our awareness and with little accountability
(c) Data driven optimisation involves a range of subjective decisions and any optimisation will benefit some citizens and marginalise others.
(d) Digital inclusion and access to informational systems are no guarantee of social inclusion or equal distribution of outcomes

The dominant approach in most smart city projects facilitates a top-down centralised and algorithmic administration of a city in the interests of the economy and security. Smart technologies can improve citizens lives, but the dominant data extraction and prediction imperative means that the systems are asymmetrical with regard to information. Further, they require, or in some cases force, citizens to trade services for data privacy and control. The data shadow component of our digital footprint is growing and the conditions under which it is developing are largely hidden from us. An alternative approach is needed.

A desire to rethink and redesign the socio-technical and economic structures of contemporary surveillance systems is emerging. Some are foregrounding normative ideals and focus on a good society or the conditions for a good life. For example, some academics have been developing an argument in support of 'good' work conceptualised as work that enables creative autonomy, human fulfilment and is remunerated adequately (Hesmondhalgh and Baker 2011; Banks 2007). In public policy we see a range of ethical guidelines that foreground 'human autonomy' in relation to the development of a good AI society. The 2019 guidelines from the High-Level Expert Group on Ethics and Artificial Intelligence state that 'AI systems should both act as enablers to a democratic, flourishing and equitable society by supporting the user's agency and foster fundamental rights, and allow for human oversight (HLEG 2019).[5]' Explainability is a key principle of the AI HLEG guidelines, and they define it both in relation to how intelligible the system is, and how accountable it is (Floridi et al. 2018). Sociological and critical communication approaches tend to focus on human empowerment, capabilities and social justice (Couldry and Powell 2014; Mansell 2016, 2017; Couldry 2019). This approach to empowerment refers "to the capacity of individuals, communities and/or groups to access **and use** their personal/collective power, authority and influence, and to employ that strength when engaging with other people, institutions or society" (Pierson, 2012:102). It remains to be seen if these aims and guidelines can move beyond discourse and performance to effectively change practices on the ground.

If we want to foreground human flourishing, well-being and freedom, and seek to retain democratic principles and social justice, we need to reimagine how we approach smart city projects and what they are for. Mansell (2016) for example notes that two imaginaries inform the dominant approaches to digital governance: market-led and state/market led. She suggests that a third more collaborative commons-based imaginary is possible and could provide a more empowering form of governance and draw upon more horizontal forms of communication. We suggest that we can reimagine the smart city as a communicative space where the citizens are positioned as peers with the city administration. A city in which the asymmetry of the panopticon is replaced by a more symmetrical form of information flow, communication and governance wherein the citizen is able to see, understand, control and track the data the city has captured on them, and is also able to contribute to the selection, or deselection, of optimisation processes. Such a citizen-city relationship puts two-way communication and the concept of locality – understood as a basis for communication – at the core of smart city design.

In positioning a two-way peer-to-peer communication at the core of smart city design it is instructive to learn from research on human face-to-face dialogue, in particular, the concepts of common ground, or mutual knowledge, and the process of grounding (Clark 1996). In human dialogue grounding is a process whereby groups of individuals work together to develop a shared understanding, and this understanding is grounded by the mutual belief between participants that all participants have a 'clear enough' understanding for the group dialogue to move forward. An utterance that has not been acknowledged as understood by the other participants does not constitute a contribution to the common ground, and as such cannot be used to progress the dialogue. The efficiency of the grounding processing within a human-human dialogue is partly due to the variety of acknowledgment mechanisms that can be used (for example, head nodding, or eye gaze); and, also to the principle of least collaborative effort which means that a speaker attempts to make their utterances as brief and informative as they can so that their partners can minimise the effort it takes to process and acknowledge them. Furthermore, research on grounding in human-robot communication has found that the grounding process can be strengthened if the robot reveals what it has internalised to its human participant (Schutte, Mac Namee, and Kelleher 2017).

[5] See AI HLEG, Ethics Guidelines for Trustworthy AI. High-Level Expert Group on Artificial Intelligence and the European Commission (Brussels), 2019. https://ec.europa.eu/digital-singlemarket/en/high-level-expert-group-artificial-intelligence

Integrating the grounding process, the principle of least-collaborative effort, and the lessons from human-robot dialogue within the communication dynamic of a smart city/citizen would imply that:

- a city should not capture, use or repurpose data relating to an individual without the citizen having the capacity and means to acknowledge that they agree to this,
- the process of requesting an acknowledgment from a citizen should be as informative and brief as possible (but ongoing and meaningful)
- the smart city should be intelligible and transparent to citizens with respect to the data that it has gathered, used (and inferred) about them.

With respect to transparency the concept of intelligible transparency is important (O'Neill 2013). For a smart city to be transparent, it is not enough to simply make data available. To be truly transparent a city should work to make this data intelligible. This involves being proactive in helping citizens to understand how, when and why the data was collected, and also to what purposes it could be used for, including the potential harmful outcomes that the data could contribute to, such as predictive privacy harm (Crawford and Schultz 2014; Barocas and Nissenbaum 2014), and data determinism (Ramirez 2013). The benefits of this type of intelligible transparent collaborative communication between a city and its citizenry regarding the data it collects and how it uses it has the potential to not only improve the trustworthiness of the city but also, as (Greenfield 2013) notes, to unlock the creative abilities of the citizens to develop new solutions to problems faced by themselves and their fellow citizens. Viewed in this way, the smart city can be understood as a platform for the development of new forms of contributory economy. It can also be understood as a basis for providing clear lines of accountability regardless of whether state, private or other actors are involved. Both transparency and accountability are core to explainability, as defined by the AI HLEG in 2019.

A reimagining of the citizen-city interaction as a dialogue between equals may provide a useful starting point for addressing some of the serious ethical, social, political and environmental problems with current smart city designs and implementations. Building on this we argue that understanding the data shared between the citizen and the city as the common ground for a dialogue directs our attention to the range of constraints placed on mutual understanding by current structures and the lack of voice afforded to citizens and inhabitants. Without common ground, and mutual understanding, the citizen is repositioned as the object of surveillance and an inhabitant in a panopticon, as distinct from a participant in a dialogue. For a citizen to be able to engage with the city in a dialogue about their lives, they must know and control their digital footprint (or common ground) that is the basis for their communication with the city and the city's communication with them. Or a trusted third party could do this on behalf of the citizens. To empower and represent a citizen in this way requires the smart city infrastructure (and a range of other data services) to be transparent in terms of how they collect data, and what they do with it. Citizens must be provided opportunities to ground (or not) the dialogue and update the data that has been collected of them, and also to understand and control the uses to which this data is put. Finally, consideration needs to be given to the capabilities of citizens to participate and understand the dialogue, and the outcomes for them if they cannot. In these circumstances a robust governance structure that rebalances data extraction and prediction in the citizen interest and constructs clear lines of accountability is needed.

Conclusions

The Anthropocene is caused by the interrelationship between the rapid acceleration of thermodynamic entropy, the quest for total certainty in AI driven data management systems (or zero entropy in information terms), and an ecological crisis. The current pandemic is only increasing our consumption of energy amid demand for mediated forms of work, leisure and communication. In addition, we are now seeing a rush by state and corporate entities to develop Covid-19 contact tracing apps. This rush is occurring without adequate structures to protect autonomy or provide transparency and accountability. Under such conditions there is little time to build common ground, assess the technical limitations or social risks, or consider the uneven distributional impact of these changes. Zuboff (2019) noted that the state of exception following September 2011 enabled state and corporate interests to introduce many of the surveillance technologies which underpin today's surveillance capitalism. The current state of exception could easily normalise new levels of surveillance and fundamentally change our relationship with our data that will persist long after the crisis has passed. Indeed claims that AI can solve social problems if only enough data is collected are doomed to fail and may in fact embed a form of 'functional stupidity' within smart city solutions (Stiegler 2012; Fitzpatrick and Kelleher 2018).

The paper has highlighted that optimisation and the prediction imperative are at the core of the technologies that underpin commercial smart city projects and the more generalised culture of surveillance. Despite its positive connotations, optimisation is not in and of itself a positive for city inhabitants. Any optimisation will prioritize one set of values, outcomes or individuals, and marginalise others. All optimisation processes involve a range of human choices and most involve assumptions based on past events and a tendency to gather more and more data. Consequently, before any optimisation is acted upon it is important that a clear understanding of who benefits and who is marginalised is developed. It is also crucial that we go beyond technological solutionism to the issue of discrimination and give meaningful attention to democratic oversight and accountability. Current approaches to transparency and accountability exist largely as abstract principles and current solutions focus only on explaining the technical process while ignoring the human decisions along the way. To date the efforts at public participation and empowerment in smart city projects have resulted in increased levels of data extraction and prediction rather than citizen empowerment, equally distributed social outcomes or consideration of the ecological burden.

This paper is not arguing for a recasting of smart city engagement with citizens as one of individual responsibility and choice. If we are to build 'common ground' between citizens and civic infrastructures and start to approach the ideal of freedom to attain human flourishing and well-being, then digital inclusion and public engagement initiatives need to go beyond platitudes, freedom to choose between services and skill building for the few. The citizen-city relationship needs to be reframed as one of peer-to-peer communication where the citizen is empowered to understand their digital footprint, the city works to collaboratively ground and make intelligibly transparent the data it has collected and used, and both can monitor the differential impact of these activities on the economic, social and environmental life of the city.

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