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Data-driven urban management: Mapping the landscape

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ABSTRACT

Big data analytics and artificial intelligence, paired with blockchain technology, the Internet of Things, and other emerging technologies, are poised to revolutionise urban management. With massive amounts of data collected from citizens, devices, and traditional sources such as routine and well-established censuses, urban areas across the world have – for the first time in history – the opportunity to monitor and manage their urban infrastructure in real-time. This simultaneously provides previously unimaginable opportunities to shape the future of cities, but also gives rise to new ethical challenges. This paper provides a transdisciplinary synthesis of the developments, opportunities, and challenges for urban management and planning under this ongoing 'digital revolution' to provide a reference point for the largely fragmented research efforts and policy practice in this area. We consider both top-down systems engineering approaches and the bottom-up emergent approaches to coordination of different systems and functions, their implications for the existing physical and institutional constraints on the built environment and various planning practices, as well as the social and ethical considerations associated with this transformation from non-digital urban management to data-driven urban management.

1. The digital revolution

Today, more than half of the world's population live in cities and, by 2050, this is predicted to increase to more than two-thirds (United Nations, 2018). It is only in the last 25 years that human habitation of the planet has become predominantly urban and, at this point, society has shifted to a post-industrial, information era. There are many aspects to this shift, not least the pace of urban sprawl in emerging economies, the transition of employment into knowledge-based sectors, radical improvements in population health, reductions in mortality, increased longevity, and increased educational attainment. At the same time, this transition has given rise to a range of new challenges associated with managing populations living in urban agglomerations. The underlying economy has seen globalisation and the automation of previously labour-intensive industries. These changes have paralleled social, political and economic developments in terms of reductions in absolute poverty, a growing middle class, but also led to radically increasing inequalities due to the richest in society becoming even richer. These complex and interdependent phenomena are among the challenges facing urban management today.

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At the basis of many of these social and economic changes lie the information technologies and networked communications of contemporary society (Castells, 2000). However, these same technologies also create opportunities to address many of the challenges found within fast-paced, complex urban environments. The ongoing 'digital revolution' provides opportunities in light of 'real-time evidence' for urban professionals and policymakers to make better decisions in managing public assets and delivering services (Mans, Giest, & Baar, 2018; Meyer, Crowcroft, Engin, & Alexander, 2017). There are, however, two main challenges associated with the radical increase in data availability and processing capacity: first, the technical and analytical challenges associated with the sheer volume of data and its heterogeneity; and second, the significant ethical and regulatory implications of gathering and analysing these types of data.

This paper attempts to provide a transdisciplinary synthesis of the 'landscape' of urban management by integrating different aspects of the fragmented literature on data analytics and cities, as well as the policy practice. We combine perspectives from computer science, geography, urban planning, and architecture, to increase our understanding of the opportunities and pitfalls of 'big' data and emerging technologies in the urban domain. We start by contextualising 'data-driven urban management' in Section 2. In Section 3 we subsequently give an overview of available data sources and data sharing practices, data processing procedures, ethical and privacy considerations, and available technologies enabling citizen-government interactions. Section 4, in turn, relates these developments specifically to urban management functions and services in three categories:

1. **Real-time management** – corresponding to actions based on dynamic data usage with a short time delay (often due to transmission and processing) related to activities usually over diurnal, weekly or, at most, monthly time scales – e.g. traffic flow management.
2. **Evidence-based planning decisions** – corresponding to actions based on longer-term projections processing mainly historical data, which pertain to the longer-term strategic role of forecasting for urban planning – e.g. predicting population trajectories to plan for new schools, hospitals etc.
3. **Framing the future** – corresponding to the design and creation of alternative futures, and through traditional and new methods of problem-solving associated with designers and political decision-making.

Against this background, Section 5 discusses the future of data-driven urban management.

2. Urban management in context

Urban management is an elusive concept (Kearns & Paddison, 2000; Stren, 1993; Werna, 1995). Some understand urban management to be a loosely coupled set of policies, plans, programmes and practices that try to ensure access to public services (Davey, 1993), while others perceive urban management as a synonym for public administration. And where Mattingly (1994) considers urban management as an exercise of responsibility to improve the efficiency of a city, Bačlija (2011) has (re)conceptualised urban management as a reform of city administration that aims to establish a balance between social and economic development. Thus over the past years, it seems, the term urban management has been actively used for a variety of issues related to planning, administration, and regulation of (complex) urban environments. The relatively loose understanding of what exactly is urban management signals that there is most likely no singular definition possible that covers all different understandings without becoming meaningless. However, because the term is widely used it becomes important to unpack it. One way of doing this is by drawing parallels with the much more well-defined concepts of project management and programme management.

At its core, the idea of project management is to ensure that a sequence of tasks and elements are brought together as efficiently as possible to attain a certain predetermined desirable outcome; typically within time and costs constraints (Packendorff, 1995). In turn, programme management can be considered as the amalgamation of multiple projects and can be defined as: "*the integration and management of a group of related projects with the intent of achieving benefits that would not be realised if they were managed independently*" (Lycett, Rassau, & Danson, 2004, p. 289). The desired outcomes of the individual projects, in turn, are aligned with and informed by the overarching vision that guides the programme.

For this paper, we consider urban management as the spatial equivalent of programme management. Because of its spatial reality, urban management operates within a set of constraints that have been inherited from previous 'irreversible' iterations of the 'management and planning' cycle. The irreversible aspect implies that the urban form often requires adaptation to, or replacement for, new functions. Hence the need for management. As such, urban management is driven by a vision that politicians and policy practitioners aim to bring into effect, whilst having to manoeuvre through the historical fabric of existing infrastructure, communities, and policies that have impacted and continue to impact on the space that urban management tries to control or govern in the first place. At the same time, urban management itself acts on space in a strongly emergent way: modifications made to the urban fabric will, in turn, lead to both the expected and the unexpected, as well as desirable and undesirable outcomes; urban management tries to affect changes in an environment that simultaneously constrains and facilitates these changes. Urban management can thus be considered a process with a high degree of complexity and uncertainty that has a symbiotic and emergent relationship with urban space.

The characterisation of urban management as a process with a high degree of complexity and uncertainty that acts upon space show many similarities with urban planning. We argue, however, that urban management is a part of the urban planning cycle but at the same time has a different focus. Whereas the wider planning process consists of the collective "orderly sequence of action" of the public, stakeholders, and the government aimed at improving the urban environment (Hall & Tewdwr-Jones, 2010, p. 3), urban management is less orderly, more volatile, and has the task to tackle urban issues both within and outside the scope of the concepts

Table 1
The urban management data landscape.

Classification	Examples	Studies
Personal data	Official records with details on households, education, immigration status. Also, other personal data such as consumer transaction data, social media usage, and mobile phone data.	Using loyalty card data to study consumer mobility patterns (Lloyd & Cheshire, 2018)
Proprietary data	Data not freely available in the public realm but owned by, for example, banks and other consumer-facing organisations. Some of this may be personal data.	Estimating human activities using Wi-Fi probe data (Kontokosta & Johnson, 2017); investigating ethnic segregation using Consumer Registers (Lan, Kandt, & Longley, 2019).
Governmental data	Data owned by government institutions like police departments and the Home Office.	Police officer patrolling data (Wise & Cheng, 2016); immigration management using administrative data (Batalova, Shymonyak, & Mittelstadt, 2018).
Open and public data	Open data are free for everyone to use and, for instance, available through government platforms (e.g. data.gov.uk). Public data are part of the public domain but has access restrictions (e.g. Ordnance Survey map data).	Planning support system using various open data (G. Zhang, Zhang, Guhathakurta, & Botchwey, 2019); open data integrated city dashboard (Gray, O'Brien, & Hügel, 2016)
Organic and crowdsourced data	Organic data are by-products of services that have some form of public value, whereas crowdsourced data include user-generated web data, for example, through Wikipedia, OpenStreetMap, or social media (including YouTube, Twitter, Instagram). Some of this may be open data.	Geodemographic classification using Twitter data (Longley, Adnan, & Lansley, 2015); urban form analysis using OpenStreetMap (Boeing, 2018).

and ideas set out in the larger planning vision. We, therefore, agree with Lai (2013), who suggests that urban management focuses on both decisions and plans, whereas urban planning emphasises plans.

The context in which urban management operates, however, has evolved dramatically in recent years, particularly in the era of novel data sources and technologies (Geertman, Allan, Zhan, & Pettit, 2019). This brings us to the more recent development of 'data-driven' urban management (Townsend, 2015), in which new data and technology intersect with the issues urban management is concerned with. Urban management therewith becomes very close to, yet another, difficult to define term: 'urban analytics'. As Michael Batty (2019, p. 403) writes: "*Urban analytics is one of those clichés that seems to effortlessly roll off the tongue as though we have used it all our lives. It strictly originates from 'urban analysis', but it is more than this for the term analytics implies a set of methods that can be used to explore, understand and predict properties and features of any system, in our case of cities.*" Data-driven urban management as such becomes the implementation of new data, technologies, and advanced analytics that aims to facilitate the efficient management of urban areas.

3. Data and technologies

Over the past decade, a plethora of new data sources has become available for urban management, opening up many new possibilities to better monitor and understand urban settings – moving from a 'data-scarce' to a 'data-rich' environment (Miller & Goodchild, 2015; Verhulst, Engin, & Crowcroft, 2019). Yet, at the same time, the relevant data landscape is largely uncoordinated and suffers from a range of infrastructure issues both in technology and policy terms. We loosely categorise these available data sources into personal data, (other) proprietary data, government data, open and public data, and organic and crowdsourced data (see Table 1). This categorisation is mainly based on the ownership and accessibility of these data sources; however, it should also be noted that this categorisation is non-exhaustive, and categories are not *per se* mutually exclusive.

Personal data refers to "*any information relating to an identified or identifiable natural person*" as defined in the EU General Data Protection Regulation (GDPR). Although there is no definitive list of what is or is not personal data in the literature or in the legislation, within the more practical urban context we interpret this as the combined data from all official records (household, education, employment, health, immigration, crime, etc.) and other digital breadcrumbs that individuals leave through everyday activities (banking, shopping, web browsing, etc.). Other proprietary data, on the other hand, are data that is owned by an individual or organisation that gives a competitive advantage (WiseGEEK, n.d.). Examples of proprietary data include banking, retail, online platforms data or other forms of consumer data, which are often collected at population level and involve significant irregularities in terms of representation in particular (Longley, Cheshire, & Singleton, 2018).

Governmental data refers to data collected primarily by government departments and other related organisations for registration, transaction and record-keeping, usually during delivery of a service (ADLS, n.d.). This can essentially be seen as personal data used at aggregate level to produce official statistics, hence safeguarding procedures apply when access is needed at higher levels of granularity. Open data, on the other hand, comprises data that is freely available for anyone to access, use, modify, and share for any purpose. Government data platforms (e.g. data.gov in the US, data.gov.uk in the UK, etc.) are known to be the main open data providers. Public data is similar to open data, but access might be restricted due to sensitivities and costs involved in producing such datasets (e.g. Ordnance Survey). Lastly, organic data (in contrast to 'designed data') refers to cumulative data recoded through automated tracking of transactions of all sorts – such as data produced by web search engines, social media, traffic cameras digitally counting cars, scanners recording purchases etc. (Groves, 2011). Data streams in this category often have no meaning themselves until users explore them to find answers to their questions. A related category is crowd-sourced data which is collected by harnessing the information and skills of large crowds of people on collaborative projects such as Wikipedia and OpenStreetMap.

Because of this changing and diverse landscape of data available to researchers and planners, and the different nature of the type of data available, a number of issues require attention: data sharing and integration processes, processing and knowledge generation processes, and user interaction technologies.

3.1. Data sharing and integration

Urban researchers and policymakers are often interested in bringing together datasets from disparate sources. At the same time, exploitation of data by various stakeholders is becoming a growing public concern, especially after recent major data breaches (e.g. Facebook/Cambridge Analytica). From a good governance perspective, and given the governments' unique legitimacy to collect and process citizen data also brings with it a high degree of accountability, the traceability of the data sources and the processing methods applied to these sources throughout the policy-making stages is crucial. In the United Kingdom, the importance of data sharing and integration methods is exemplified by the Digital Economy Act 2017. This Act partly aims to promote protected data sharing and provide government departments with the necessary information to propose and implement policies and services without compromising data privacy and security. Similarly, the General Data Protection Regulation (GDPR) of the EU also aims to primarily give control to individuals over their personal data and to simplify the regulatory environment for businesses accordingly; although there are no clarifications on the technology implications arising from fairly loaded concepts introduced such as data 'ownership', 'portability', 'right to rectification and erasure', 'transparency', etc. There is, therefore, growing social and policy pressure on the technology community to produce solutions to manage: (1) the digital identification of the users of the data, for instance using biometrics and mobile devices; (2) data ownership as well as the tracking of this ownership across all processing stages; (3) data transactions involving the exchange of data between devices or platforms; and (4) privacy and security (Zoonen, 2016). Elements of blockchain technology could especially have far-reaching potential in secure and trusted data storage and transaction operations within the urban management context (Treleaven, Brown, & Yang, 2017).

3.2. Data processing and knowledge generation

The quality of data processing and the reliability of any insights derived from advanced analytic processes are often strongly correlated with the initial data quality during collection and the choice of data representation. Yet, many new data sources differ from more conventional surveys and large-scale data collection efforts and are harvested from a variety of sources rather than collected using scientifically sound methods. As such, data-driven research has been criticised for being too 'soft'. Main issues are the sometimes-dubious provenance of the data sets, the quality of the data, and the often-biased nature of the data. This requires not only careful understanding and 'hardening' using both internal and external validation techniques (Goodchild, 2013) but also expert knowledge on the context in which the data have been acquired and on the particularities of the data sets themselves. Data hardening processes typically involve various stages of data wrangling, cleaning, editing, normalisation, transformation, and feature extraction and selection. In addition to rigorous data cleaning and data preparation methods, the inherited biases and limitations of the data should be well-documented before the data can be repurposed to support urban management decisions (Longley, Cheshire, & Singleton, 2018).

An example of repurposing big data to assist urban management and planning is described by Lansley, Li, and Longley (2019). The high costs and infrequent update of decennial censuses underpin their recent initiative to re-purpose consumer and administrative data to statistics at more frequent time intervals and a higher spatial granularity. These 'Consumer Registers' are compiled from both public versions of Electoral Registers and other consumer data sources, recording people's names and addresses. Affected by a non-transparent data compiling process, Consumer Registers are, however, of unknown provenance. Lansley et al. (2019) therefore have proposed fuzzy address matching and linkage of names and address over time to estimate housing relocations. They have also cross-referenced the population counts and addresses with external sources, such as the 2011 Census population data, the Office for National Statistics mid-year population estimates, and Land Registry address data. In this sense, these 'linked consumer registers' are a highly granular and viable alternative to more general administrative records.

The variety of data flooding in, together with the increasing complexity of cities (see for example Batty & Marshall, 2012), also demands methods that can manage these levels of complexity. Not surprisingly, this has resulted in a burgeoning literature applying machine learning algorithms on urban data to support urban planning and management decisions. The most obvious examples of this can arguably be found in the domain of transport studies where machine learning techniques have been implemented to model modal choice distributions (e.g. Aschwanden et al., 2019) or to classify GPS data (e.g. van Dijk, 2018). It is not just the transport domain that greatly benefits from these developments, and machine learning methods are implemented to assist with all types of other urban management challenges found across the globe. Recent studies, for example, have used machine learning to assess the quality of streets in China through image recognition techniques (Ye, Zeng, Shen, Zhang, & Lu, 2019), predict daily and weekly waste generation at the building scale in New York (Kontokosta, Hong, Johnson, & Starobin, 2018), and forecast possible slum formation (Ibrahim, Titheridge, Cheng, & Haworth, 2019).

Where big data analytics provide the opportunity for examining large and varied data sets to uncover hidden patterns, unknown correlations, customer preferences etc, it does, however, require a massive paradigm shift in the way scientific knowledge is created, utilised, and implemented – focusing more on the '*what?*' question through theory-free models rather than the '*why?*' question. Given that urban management problems often have large degrees of complexity and an enormous range of time scales, potential usefulness of data-driven approaches becomes obvious. Beyond the fundamental difference in the type of research questions that the new data-driven approaches answer in comparison to traditional methods, there are some core challenges which question their academic grounding such as (1) the use of “correlation” instead of “causation” as the basis of analysis; (2) the “reproducibility” issue referring to the fact that the outcome of such analysis is likely to change each time a different dataset is used since that data itself is used for the explanation; (3) the “traceability” issue referring to non-comprehensible processes that produce such outcomes – essentially no intermediary stages during analyses are accessible to human experts; and (4) the inherent “sampling” issues within the training data since data available at the population level are usually not representative and contain many bias factors that may distort the outcomes.

3.3. User interaction

Contemporary urban challenges usually require the collaboration of multiple disciplines, sectors, and geographic locations; and they rely more heavily than many other fields on collaboration between the general public, professionals and experts. The usability of any technologies addressing the needs of this diverse stakeholder landscape is, therefore, a key concern. Platform technologies (Government data platforms, simulation tools, city dashboards etc.) and conversational AI systems – such as chatbots and ‘intelligent’ assistants (Lommatzsch, 2018) – are increasingly utilised as key interaction tools within the urban domain (Moore, 2017). Beyond the wide range of existing visualisation techniques (Ferreira et al., 2015; Shen et al., 2018), BIM (Building Information Modelling) and Digital Twins (Batty, 2018) are also emerging as interesting concepts – both essentially referring to the evolving digital profiles of physical objects or infrastructure allowing greater monitoring and prediction capabilities. Beyond the geometry of buildings, BIM also covers spatial relationships, light and energy analysis, geographic information, and other quantities and properties of building components and materials providing comprehensive control over the whole life-cycle of construction (Pärn, Edwards, & Sing, 2017). The idea of a Digital Twin, on the other hand, is a more general term emerging in parallel to the growing deployment of IoT systems (Parott & Warshaw, 2017).

3.4. Ethical considerations and challenges

The availability of large amounts of personal data together with ever-increasing storage capacity, processing power and analytics capabilities makes individuals more and more predictable, and less and less discrete to private multinational companies, governments, individuals, and machines. With the wider deployment of IoT systems, even more granular data will become available through both human and machine activities. Although major data breaches, such as the Cambridge Analytica/Facebook case, and the introduction of the EU's General Data Protection Regulation (GDPR), gave way to a growing public awareness around digital trust, privacy and data ownership/exploitation issues, the relevant technology and policy landscapes are still far from providing a clear vision. Two notable developments in this context are; first, the rise of Privacy Enhancing Technologies (PETs) along with data minimization, anonymization, and encryption approaches; and second, technologies that are being developed to handle data transactions. Blockchain distributed ledger and smart contract technologies, in particular, are emerging as the facilitators of such developments at the foundational level. The ethical issues regarding the processing and analytics stages range from inherent bias embedded in historical datasets that are used to train the current systems, to the understanding of algorithmic insights, and the human involvement in the process. Political context around such developments should also be mentioned (Ruppert, Isin, & Bigo, 2017) – for example, where Asian society has a benevolent view of government and expect them to collect data on citizens for the ‘management’ of society, in contrast, Western society prioritizes the privacy associated with individuals and the ethical behaviour of technology. Associated ethical implications and concerns have also found wide coverage in recent literature (Liang, Das, Kostyuk, & Hussain, 2018; Stucke & Grunes, 2016).

4. Data-driven urban management

The opportunities that new technologies and data sources are bringing to the urban domain are all-pervasive and all-embracing, ranging from monitoring and managing all types of infrastructure and flows in real-time to smarter prediction of what is to come, and to imagining, designing and testing of possible futures. This digital transformation affects the practice of urban management in at least three ways (see Table 2 below) through its impact on real-time management, evidence-based planning, and the framing of the future.

4.1. Real-time urban management

A key impact of the new data sources and technologies is the potential to generate near real-time actionable knowledge for a diverse range of city functions and services (Engin & Treleaven, 2018). While accurate real-time information increases interoperability, it also enables more efficient monitoring, maintenance, intervention and regulation of service and public records. Concepts such as ‘nowcasting’ are enabling high-quality short-term predictions to manage and understand flows of people (Aschwanden et al., 2019) and local council service needs (Kontokosta et al., 2018). Organic web and social media data may also provide invaluable real-time insights into the public sentiment around the current developments. Arguably, however, most comprehensive and high-quality urban data relates to transport and mobility, hence making the topic well suited for experimenting with real-time operations and services (Gallotti & Barthelemy, 2015).

Table 2
Urban management and service provision.

Real-time management	Evidence-based planning	Framing the future
Monitoring urban activities and flows (Aschwanden et al., 2019) Emergency interventions (Usher, Hodge, Amin, & Lee, 2016) Public opinion (D'Andrea, Ducange, Bechini, Renda, & Marcelloni, 2019) Personalised citizen services (e.g. healthcare) (Kontokosta et al., 2018) Monitoring and maintenance of urban infrastructure (Lee et al., 2016)	Infrastructure improvements (Boeing, 2018) Responsive city and urban resilience (Klein, Koenig, & Schmitt, 2017) Future service demands and transport modelling (Anda, Erath, & Fourie, 2017; Batty et al., 2013) Urban environment assessment (Ye et al., 2019) Migration and demographic change (Lan et al., 2019) Employment and inequality (James, 2018) Economy and sector projections (Garcia, 2019) Crime prevention, public safety, and security (Wise & Cheng, 2016)	Government – citizen – business interactions (Gagliardi et al., 2017) Human-machine and machine-machine interactions (Hammoudeh & Arioua, 2018) Physical and virtual space interactions (Kamel Boulos, Lu, Guerrero, Jennett, & Steed, 2017) Future Mobility Survey (Cottrill et al., 2013) Networks and communications (Castells, 2000) Business processes and productivity (C. Zhang, Wu, Zhou, Cheng, & Long, 2018) Evolutionary process (e.g. cognitive shifts, technological singularity) (Markou, 2019)

A good example of real-time mobility management can be found in Singapore (Lee, Kwon, Cho, Kim, & Lee, 2016). Singapore enhances its overall transport system through its Intelligent Transport System (ITS) working together with other transport initiatives such as free public transportation in-pre-morning peak hours, a vehicle quota system, well-functioning public transport system and congestion charge. On its comprehensive ONE.MOTORING portal, citizens can access information collected from surveillance cameras installed on roads and taxi vehicles with GPS, and through Traffic Smart, snapshots of roadways taken at every 5-min interval are made available to drivers (real-time moving video and close-up shots are not provided due to security reasons). The Land Transport Authority (LTA) uses surveillance cameras to look out for road incidents and if one is detected, LTA activates the vehicle recovery crew to reach at site in 15 min. LTA's Parking Guidance System provides drivers with real-time information on parking availability and the MyTransport.SG smartphone application provides real-time information for commuters. Besides Singapore, also Milton Keynes, Southampton, Amsterdam, Barcelona, Madrid, and Stockholm are among major cities that have implemented smart city technologies and programs (Saunders & Baeck, 2015).

City dashboards are also being fashioned to bring real-time data to the attention of commentators and decision-makers so they can synthesise an integrated view of their domain. So far such dashboards are quite patchy in that they collapse many different and often non-comparable or non-integrable data sources into forms of viewing platform but their analytic capability is not in doubt and a number of such dashboards are being embodied with GIS functionality, and other modes of basic analysis. Review articles by Gray, O'Brien and Hugel (2016) and by Batty (2015) define the state of the art in the development of such media. Similarly, ICT-based tools are being developed to stimulate interactions between service providers (e.g. local governments) and service consumers (e.g. citizens) (Gagliardi et al., 2017).

With regard to public records, most developed countries are investing in digital services, probably the most well-known one being e-Estonia.[1] Implementations can also be found in Singapore's SingPass single sign-on system[2] which provides access to a holistic range of government services, such as a citizen's electronic health record; the UK's ‘digital by default’ strategy (Cabinet Office & Government Digital Service, 2014); Germany's *Bundesagentur fur Arbeit*,[3] virtual labour market platform to reintegrate job seekers into the labour market; and India's *Aadhaar*[4] unique identity card.

Lastly, chatbots and ‘Robo’ advisors are also increasingly deployed by governments. For example, the US Department of Homeland Security uses a virtual assistant, *Emma*,[5] to respond to citizen enquiries. Chatbots and virtual assistants could give citizens up-to-date local information (events, holidays, road conditions, waste collection etc.) on a 24/7 basis, help them find relevant government data and information online, fill in the forms (renewal of driving licences, applications for pensions and other relief packages, filing of taxes etc.), dispense accurate and up-to-date information about medical aid schemes, local hospitals, and emergency healthcare protocols etc., handle complaints and generate awareness about regulations and legislation, and guide tourists to local attractions and plan itineraries (Farkash, 2018). Other interesting real-time applications of data science technologies for the urban domain include online dispute resolution systems, automated infrastructure maintenance, and delivery of contracts and transactions (Fox, 2016).

4.2. Evidence-based planning decisions

A contemporary challenge facing city government is to gain public acceptance of steps needed to achieve a more sustainable future. The problem is that all too often local interests can block plans needed to create a more sustainable global system. It is remarkably hard, for example, to gain public acceptance of a plan to rationalise a healthcare system if that means closing a local hospital. The hope of evidence-based planning is that by presenting the public with evidence in an easily understood form that it will

[1] https://e-estonia.com.
[2] https://www.singpass.gov.sg.
[3] https://www.arbeitsagentur.de.
[4] https://uidai.gov.in.
[5] https://www.uscis.gov/emma.

be possible to shift the debate from NIMBYism and inertia, to discuss the benefits of new plans. This is a matter of defining a vision for the future, and then using evidence and analysis to test options in such a way that some degree of consensus can be achieved on the best way forward. One of the challenges that this approach has come across in the past is that local populations tend to know and understand their local areas better than policy professionals; however, they are typically unaware of alternative solutions that have successfully been implemented elsewhere. This creates a democratic deficit that lies behind the tendency towards NIMBYism. It is the intention of evidence-based planning to overcome this by empowering local communities through giving them access to the evidence needed for them to arrive at a constructive vision of the future themselves.

In urban and regional planning, good practice involves the use of models and various other analytic tools to explore 'what if' kinds of scenarios in the context of current political acceptability and viewpoints. For instance, Land Use Transport Interaction models such as QUANT[6] use spatial interaction modelling techniques to simulate the impact of changes in population, employment, and transport costs on land use. The model output can be used as data-informed evidence to evaluate policy alternatives. Accuracy of longer-term projections is often strongly correlated with the amount as well as the quality of all the evidence entered into the system. This bolsters the case for both the traditional modelling approaches to be combined with the new 'data-driven' approaches. Space-syntax, on the other hand, represents an entirely different class of theories and techniques for the analysis of spatial configurations. These ideas potentially offer more space in the theory to incorporate the advantages of new data sources which emerge from a much finer spatial scale where human behaviour is easier to observe (Hillier & Hanson, 1989; Porta, Crucitti, & Latora, 2006).

The role of data-driven technologies and analytics for longer-term planning decisions in general, however, may seem less clear compared to automated real-time management and coordination functionalities. Yet, the ability to record and process large amounts of data from a variety of sources can provide inputs to speculation about the future. For example, dashboards can be used to track and visualise the trends associated with various urban indicators (Kitchin, Lauriault, & McArdle, 2015). Insights derived from these long-term trends, possibly with a high spatial and temporal granularity, can provide a useful 'evidence-base' for planning decisions. This fits within the ideas proposed by Batty and Marshall (2012) who argue that urban planning has moved away from top-down models that view cities as aggregated equilibrium systems. Building on complexity theory, they argue that cities are actually continuously out-of-equilibrium with their structure emerging from the bottom up.

Bottom-up approaches to understand city structure and development challenge the traditional idea of the 'optimum city' and therewith requires temporal dynamic data; the existence of well-established research groups such as the Future Cities Laboratory[7] based at ETH Zürich and the Singapore-MIT Alliance for Research and Technology[8] are logical responses to this requirement. The Future Cities Laboratory, for instance, has a workstream dedicated to 'evidence-informed urban design and planning processes' which works on the development of methods and tools to transform data from a variety of sources. Recent and diverse examples are found in the realm of using social media data to better understand human activity and interactions in a multi-linguistic setting (Tomarchio, 2019), aggregating mobile phone traces for transport planning and transport demand modelling purposes with specific attention to ensuring a user's privacy (Anda et al., 2017), and in more conceptual contributions to the creation of responsive and resilient cities (Klein et al., 2017).

4.3. Framing the future

Spatial urban structures from the building to the city level are continually reinvented and re-imagined by the people occupying them, as well as containing a vast array of interactions between citizens, governments and private stakeholders. Peer-to-Peer (P2P) energy trading models provide an interesting case study to observe the development of these types of emerging, bottom-up, urban phenomena. The continuing integration of Distributed Energy Resources (e.g. rooftop solar panels) with Information and Communication Technologies (ICTs) result in traditional energy consumers becoming 'prosumers', who can both consume and generate energy (Luo, Itaya, Nakamura, & Davis, 2014). This new phenomenon of bi-directional energy flow systems introduces a number of opportunities as well as challenges ranging from new investments in the current unidirectional grid infrastructure and new energy storage solutions potentially involving everything from electric vehicles (Froese, 2018) to new business processes (C. Zhang et al., 2018) and community structures (Morstyn, Farrell, Darby, & McCulloch, 2018). Blockchain-based technologies are increasingly utilised to ensure both the security of such energy trading systems and getting rid of the need for a trusted intermediary involved in the process (Li et al., 2018), hence enabling decentralised energy sharing networks at varying spatial scales.

New service models introduced by the multinational companies such as Amazon, eBay, Alibaba, Uber and Airbnb are also shifting traditional government-citizen-private sector engagement practices. The car rental company, Zipcar, for example, has successfully established collaborations and linkage to public sector organisations (e.g. Transport for London and Driver & Vehicle Licensing Agency in the UK) to offer an alternative business model approving driver registrations within minutes and car bookings within seconds through their mobile application, hence already reducing the outright car ownership in congested urban settings. Peer-to-peer services facilitated through companies like Uber and Airbnb (Böcker & Meelen, 2017) have caused significant disruption to the existing cab/taxi (Cramer & Krueger, 2016) and hotel (Guttentag, 2015) industries. The terms 'sharing economy' and 'uberisation' emerged to refer to such hybrid market models facilitated via community-based online services. Developments in virtual reality (VR) and augmented reality (AR) are further enhancing our engagement with space and opening up a range of new and exciting

[6] http://quant.casa.ucl.ac.uk.
[7] https://smart.mit.edu/.
[8] https://fcl.ethz.ch/.

opportunities within the urban management context, such as those in personal and public arenas (Kamel Boulos et al., 2017), to enable better stakeholder participation in planning processes (e.g. neighbourhood walkability tests), mass casualty education, emergency planning and so on.

With the development of the Internet, platform technologies, mobile devices and location-based services, we have seen over the past few decades a shift towards communities emerging around social networking sites and mobile games; and services being accessed online (e.g. e-government portals, online shopping sites) while individuals are physically located at their homes, workplaces, coffeehouses and city squares (Wang, Deng, & Ji, 2017). Also, similar to the way fictions of the past became realities of the present, this 'digital turn' is likely to offer new futures that do not necessarily depend on our past experiences or the information held in historical datasets. We currently have ubiquitous data collection by large multinational companies and governments, vast quantities of digital breadcrumbs which individuals leave from a wide range of day-to-day online activities and transactions, and the increasing deployment of IoT systems making highly granular and structured data about individuals, assets and systems available in real-time. Such daily activity data are collected with portable sensors and mobile devices and investigated for transport modelling purposes, for instance, the Future Mobility Survey (Cottrill, Pereira, Zhao, & et al., 2013). When coupled with algorithmic support systems producing instant predictions and life-altering decisions affecting humans that almost certainly will have a significant impact on the framing and livability of our future cities: urban land use classifications derived from mobile phone data may significantly impact urban planning practices (Pei et al., 2014), insights into city-wide travel patterns in complex urban environments can be extracted from origin-destination taxi data (Bertsimas, Delarue, Jaillet, & Martin, 2019), and the relationship between human activity and air pollution better understood with potential implications for debates on environmental justice (Yan, Duarte, Wang, Zheng, & Ratti, 2019).

4.4. *Ethical considerations and challenges*

Ubiquitous deployment of digital systems embedded in daily life, algorithm-based services, and data analytics are creating new techno-social (Vespignani, 2009) and cyber-physical realities (Cassandras, 2016), transforming human experience in social interactions, and with physical locations, everyday items and things, and time. The availability of new data is in parallel with rising ethical concerns, ranging from the privacy and security concerns around ubiquitous data collection and smart cities (Zoonen, 2016) to amplification of bias and discrimination through algorithmic decision systems (personalisation of public services, social and economic inequalities, neighbourhood safety and policing interventions etc.). These concerns also include ethical dilemmas around the increasing human-machine (driverless car algorithm assessing options in unavoidable car crashes, social robots as caretakers/babysitters etc.) and machine-machine (e.g. home appliances communicating with retailers, driverless car communicating with city infrastructure) interactions. There are also wider debates around the democratic processes (e.g. asymmetry of information and data access privileges, manipulation of public behaviour). These include a long list which we present as follows: citizen rights (e.g. ownership and control of data, accessibility of digital services), economic considerations around business practices and income distribution (e.g. digital monopolies, taxation of digital services), perceptions around privacy and transparency as well as the 'skewed' realities (e.g. automated recommendations, manipulation of consumer behaviour), regulatory issues around legitimacy and accountability of algorithmic decisions in public decision making, cognitive shifts (e.g. loss of human navigation skills due to extensive GPS use, reducing attention span, technological singularity debates), changing nature of human-space interactions (communities formed online, AR/VR technologies etc), environmental cost of highly complex computations (e.g. Bitcoin mining) and more general social concerns around the fear of job losses due to automation and retrofitting of the new technologies into the existing infrastructure.

5. Discussion

A key consideration for the analysis of the full urban management landscape appears to be a tussle between top-down systems engineering approaches and harnessing bottom-up emergent approaches to coordination of different systems and functions. The former systems have particular attraction in terms of their apparent legibility and the potential they bring for validation of their control functions. The latter, however, may prove to be more resilient in the longer term, bringing benefits of distributed functionality, scalability and minimising the risk of single points of failure. In both top-down and bottom-up approaches, a major challenge is how to introduce the human factor into the system. In the case of systems engineering, there is a risk that without properly including frailty, the system fails due to human error. In the case of emergent approaches, a lack of explicit control can lead to confusion over responsibility for ethical standards and avoidance of inherent biases. Ultimately, the great hope for data-driven urban management is that it will create the basis for an informed and empowered community to engage democratically in the local administration of our cities and neighbourhoods.

From a research methodology point of view, a key point for the 'data-driven urban management' is the fact that "policy interventions in the real world are highly context-dependent" (Miller, 2018, p. 605). Interesting hybrid approaches in recent scholarly discussions suggest the potential use of theory-based approaches to function as the 'prior knowledge' for data-driven approaches (Ferranti, Krane, & Craft, 2017), hence providing contextual knowledge to the AI systems for example. The need to 'reverse-engineer' AI-based insights could also be another major area where the traditional theory-based insights might prove to be useful.

The pressing need in 'data-driven urban management' discussion is to develop a holistic view of the enabling technologies landscape together with their associated challenges and limitations in ethical terms, and also their potential uses as complementary technologies to ensure fairer, legal, safe and transparent behaviour of such systems. We should acknowledge the lack of discussion in this paper around the stakeholders' landscape, particularly the rise of data scientists and software developers as the new determinant actors of the urban management domain. Another missing discussion is the governance and management mechanisms around standards, licencing, and legal frameworks, which would be beyond the scope of the data and technology focus of this paper. We also derive examples from a range of different application domains to provide a unified vision around exemplary use cases for the various technologies since there is no obvious single domain that provides a complete basis for all discussions. Arguably the transport domain would be the best candidate for such a study given the availability of varied data sources and research but would still not be sufficient to provide a full basis for discussions in this paper.

6. Conclusions

The opportunities afforded by new sources of data, analytic techniques and networked infrastructure for coordination of the management of cities are only just beginning to be explored. The ambitions are wide-ranging – from providing better decision support for policymakers and personalised citizen services to automated management of city infrastructures and operations, to new collaboration models between public and private sectors. However, the scale and complexity of urban systems and institutions defy current attempts to organise them systematically. A holistic view of the full landscape is currently lacking in the literature despite the ever-growing number of high-quality research efforts in siloed disciplines, research groups and policy practice. This paper attempts to provide a reference point to fill this gap through a synthesis approach rather than attempting to provide a full systematic literature review, which would not be feasible for a topic at this scale.

Given the lack of consensus in the literature around 'urban management' and the closely related 'urban planning' terms, we employed a practical analogy to project management to contextualise 'urban management', focusing more on the practical service delivery and city functionalities under the ongoing digital revolution. We then attempted to provide a first categorisation of the available data sources (currently lacking in the literature to the best of our knowledge) based on mainly accessibility and ownership, resulting with clear usability and ethical implications. We then proceeded to provide the current approaches to 'data-driven' knowledge generation processes and user interaction technologies, followed by our conceptualisation of the urban management functions around the impact on real-time management, future planning decisions taken at present, and the previously unseen developments that change the dynamics of the urban management with new thinking and approaches. The associated ethical discussion has proven to be equally – if not more – complex than the opportunities and developments discussion. Although we attempted to provide an illustrative list of a diverse range of challenges for completeness, the topic deserves a much longer discussion in future studies.

Declaration of competing interest

None.

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