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Transportation Research Procedia 00 (2018) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2019 Mumbai 26-31 May 2019

Big data and urban mobility: a policy making perspective

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Abstract

While our lives become more and more mobile and connected, information and communication technologies allow people to move, work and maintain relationships; at the same time, some of these technologies track our habits and collect the aggregate information that constitutes big data. Research into the use of digital data, mobile phone data and ICT has for some years been showing the great potential of these sources in reading and estimating human movements through urban spaces. However, the emphasis to the manifold forms and contents of big data has not been paralleled by an equivalent attention to their potential relevance in terms of urban policy. The paper aims thus to understand and address the challenges posed by the relationship between big data, open data and urban mobility policy, investigating how big data can innovate urban mobility policy. To do so, the document refers to an extensive review of the existing academic literature on big data, focusing on mobility-related data and examining their possible relevance in the different steps that compose a policy cycle. The manifold relevance of big data emerges in relation to at least three aspects: first, the diverse sources and knowledge that big data provide; second, the different roles that data may have in the different stages of a policy cycle; third, the many actors who are involved not simply in policy issues, but also in the very production, storage and management of big data. These aspects are fundamental for defining how big data can intervene at distinct stages of a policy cycle and, consequently, help design an effective model for innovating urban policy.

Keywords: Type your keywords here, separated by semicolons ;

1. Introduction: How can big data innovate urban mobility policy?

While our lives become more and more mobile and connected, new technologies allow us to move, work and maintain relationships, even at a distance. These technologies, fundamental for participating in the life of our societies, track

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our habits and collect the aggregate information that constitute big data. Big data are "everything captured or recorded digitally by modern information and communications technologies such as networked sensors, 'smart' objects and devices, the web and social media" (Rabari & Storper, 2015, p. 28).

Research into the use of digital data, mobile phone data and ICT has for some years been showing the great potential of these data in reading fine-grained variations in urban movements over time and estimating human movements through urban spaces (Järv, Ahas, & Witlox, 2014; Kwan, Dijst, & Schwanen, 2007; Ratti, Frenchman, Pulselli, & Williams, 2006; Reades, Calabrese, Sevtsuk, & Ratti, 2007). Various types of data regarding cities, their citizens, temporary urban populations and their spatio-temporal variability are nowadays available thanks to the implementation of tracking technologies in urban studies, mobility, transport, urban planning (Birenboim & Shoval, 2016; Shoval & Ahas, 2016; Shoval, Kwan, Reinau, & Harder, 2014; Yip, Forrest, & Xian, 2016, Pucci et al., 2016), as well as the integration of novel sensing technologies (embedded in smartphones or easily connected to them). Digital data, ICT and the passive and anonymous monitoring of cell phone traffic improve our ability to understand human mobility, thanks to the ubiquity of digital devices and mobile phone networks; a 'longitudinal perspective' is available on the variability in human travel activities (Järv et al., 2014), validly complementing traditional methods.

However, the emphasis on the manifold forms and contents of big data has not been paralleled by an equivalent attention to their potential relevance in terms of urban policy. The formation process of a policy has been left in the background by the idea that, thanks to big data, "there is one and only one universal and transcendently correct solution to each identified individual or collective human need; that this solution can be arrived at algorithmically (…); and that this solution is something which can be encoded in public policy, again without distortion" (Greenfield, 2017, p. 56). The paper aims thus to understand and address the challenges posed by the relationship between big data and urban mobility policy, investigating how big data can innovate urban mobility policy. To do so, the document refers to an extensive review of the existing academic literature on big data, examining their possible relevance in the different steps that compose a policy cycle, reinterpreted under the framework of the 'experimental dimension'. The policy cycle is here taken as a reference for the process of formation of a policy since, despite its simplifications, such model allows conceiving a policy as an interrelated but not linear stages for "understanding why the policies that are in place today are the way they are, how new policies get formulated and what can, rather than could, be implemented in real-world settings" (Marsden & Reardon, 2017, p. 238). After discussing the relevance of big data in relation to urban mobility policy (section 2), the paper examines the available big data and their possible uses in each step of the policy cycle (section 3), considering also the wide range of actors involved in the issues of governance and management of big data (section 4).

2. Big data, urban mobility and policy: mapping the field

The term *big data* was first used in 2011 by the McKinsey Global Institute and, despite the lack of a shared definition (Floridi, 2012; Kitchin, 2014b; Lovelace, Birkin, Cross, & Clarke, 2016) some key features can be associated to qualify it in term of *huge in volume*, *high in velocity*, being created in or near real-time, *diverse in variety*, *exhaustive in scope*, *fine-grained in resolution*, *relational in nature*, containing common fields that enable the conjoining of different data sets; *flexible*, holding the traits of extensionality and scalability (Boyd & Crawford, 2012; Kitchin & Dodge, 2011; Marz & Warren, 2015; Mayer-Schönberger & Cukier, 2013; Zikopoulos & Eaton, 2011).
Assuming that big data is unstructured, because it comes from different sources, is stored in different databases, is not noise-free and is often incomplete, the classification proposed by Kitchin, (2014b, p. 4), based on the typology of sources producing big data, represents a relevant framework to understand its uses, potentials and limits. Because of the way big data is generated, it is the product of choices and constraints and is shaped by a system which is situational, contingent, and relational. Therefore, the following distinction changes the potentials of big data and its possible uses in urban planning and in other policy domains. Based on Kitchin (2014b), big data can be:

- *directed data* or tracking data, monitoring the movement of individuals or physical objects subject to movement by humans. It is generated by traditional 'forms of surveillance' that focus on people or places and imply a human operator;

- *automated data* is produced by automatic digital devices such as mobile phone data, capture systems, clickstream data that records how people navigate through a website or app, as well as by remotely sensed data generated by a variety of sensors and actuators;
- *volunteered data*, deriving from search and social networking activities where citizens become 'sensors' and can contribute to the collection of geographic data, thus generated by the users.

Equally relevant and connected with these issues, the algorithms and systems that are used to process and interpret the data, and thereby inform subsequent interventions, "play an increasingly important role in selecting what information is considered most relevant to us, as a crucial feature of our participation in public life… [and] provide a means to know what there is to know and how to know it, to participate in social and political discourse, and to familiarise ourselves with the publics in which we participate" (Gillespie, Boczkowski, & Foot, 2014). Reflecting a transformation already noted in relation to science (Graham & Shelton, 2013; Kitchin, 2014b; Kwan, 2016), the influence of big data may lead to data-driven forms of policy, in which data 'speak for itself', highlighting emerging issues and potential solutions to them. Nonetheless, such a transformation shows the potentialities as well as the risks (Graham & Shelton, 2013, p. 258). While some refers to the possibility of an 'automatic smart city understanding' (Villanueva et al., 2016, p. 1680), it is still necessary to have a human-based approach that considers and makes sense of such information selectively, according to the issue taken into account. In fact "only those with the wherewithal to make sense of the information (through data mining or other means of investigation) were able to increase their use of the new, digitised data" (Rabari & Storper, 2015, p. 38). Consequently, issues such as the epistemological value of big data and its necessary interactions with other forms of knowledge are object of a huge academic debate (Batty, 2013; Graham & Shelton, 2013; Kitchin, 2014a, 2014b; Kwan, 2016; Poorthuis & Zook, 2017; Rabari & Storper, 2015; Schwanen, 2017).

Big data are prone to a number of open ethical issues. The ubiquity of big data and the detail of their information question the privacy of the tracked subjects, who end up having "no place to hide" (Taylor, 2016); this may also lead to the perception of "hindered freedom", due to the pervasiveness of tracking and surveillance systems (Sager, 2006). Big data are also prone to technical limitations, due for example to the limits of the predictability in human mobility (Song, Qu, Blumm, & Barabási, 2010) and the difficult replicability of big data experimentations, due to the continuous re-engineering of platforms (Lazer, Kennedy, King, & Vespignani, 2011). Finally, big data also suffers from incomplete representation of phenomena, due for example to digital divide and the unavailability of portable technologies for specific urban populations (Graham, 2011). Such limitations originate omissions and exclusion, giving to big data a "marginalizing power" (Kwan, 2016), and specific shares of mobility practices and latent demand may remain invisible, being consequently ignored in mainstream urban mobility planning approaches (Sager, 2006).

These aspects pose some relevant challenges in relation to the effective usability of big data in urban and mobility policy, but do not question the importance of networked technologies as drivers of a real-time knowledge of mobility and urban practices and the need to understand how big data can contribute to policy formulation. A review of the existing literature confirms that, despite the significant limitations outlined before, big data use in urban management and decision making processes is conceived as a key feature of the smart city concept (Semanjski, Bellens, Gautama & Witlox, 2016; Urbanek, 2019). Big data is a novel and promising source of information able to provide deeper, more holistic and robust analysis of urban environments (Kitchin, 2014c) especially if combined and integrated with other kinds of data (Weinberg, Davis & Berger, 2012). Its disruptive potential for understanding and planning urban mobility requires to a deep change in the mainstream technical approaches to transport issues (Milne & Watling, forthcoming). For these reasons, in the last decade, several public bodies such as the EU (see ERC Mobility-spotlight projects 2018 / Analyse the mobility situation and develop scenario" in the platform on sustainable urban mob plans SUMP step 3) / chap. 1.1.2 in EC "Quality of administration a toolbox for practitioners" 2017 about data insights to help solve policy problems) and the US Congress have funded several programs to deepen the potentials of ICTs in policy making and analysis to understand their impact and issues of usability in specific areas of application, such as the mobility domain (De Gennaro, Paffumi, & Martini, 2016; Jarmin, O'Hara, 2016; Lim, Kim &Maglio, 2018). The ultimate goal has been that of promoting, into the public sector, a process of optimization and more effective management of public assets (Urbanek, 2019). The manifold experimentations conducted in the last years are at the base of a consistent series of critical ex-post evaluations on the potentials and limits of data-informed policy making (e.g. Poel, Schroeder, Treperman, Rubinstein, Meyer, Mahieu, Scholten & Svetachova, 2015; Lim, Kim, Maglio, 2018) and have been used to build theoretical insights and conceptualization of this possible integration. Thakuriah, Tilahun & Zellner (2017) pointed four major objectives linked to big data analysis in urban environments, underlining their relevance in promoting a dynamic resource management; in allowing the possibility to discover trends and to eventually analyze their developing explanation; in fostering public engagement and civic participation and, finally, in sustaining the development of "robust approaches for urban planning, service delivery, policy evaluation and reform and also for the infrastructure and urban design decisions" (p. 23). The latter perspective is shared by Semanjski, Bellens, Gautama & Witlox, 2016 who deepened this concept by noting that big data offer support for *strategic activities*, by aggregating information on time series that support and validate prediction models for long-term planning; for *tactical decisions*, conceived as the evidence-informed actions that are needed to implement strategic decisions and, finally, for *operational decisions,* giving support to day-to-day decision making activities in a short-term planning perspective.

Focusing on the mobility policy making field, two main reasons explain the relevance of big data, confirmed by the increasing importance gained, in the past years, by the concept of 'smart mobility' (Kourtit, Nijkamp, Steenbruggen, 2016). The first concerns the importance of a real-time knowledge of mobility needs and practices in contemporary cities, possible also through a more widespread use of networked technologies, as drivers of area-wide implementation of innovative urban policy and transport supply. Directed and automated data play an important role because they have different possible uses not simply to manage real time problems and address real-time operational actions (i.e. solving crisis situations such as traffic jams and accidents, or schedule adjustments in transport supply), but also as a powerful environmental, social and economic microscope (Bibri, 2017) acting as a tool for analysing trip chaining (Srinivasan & Raghavender, 2006), updating the origin/destination matrix and transport models (Noulas, Scellato, Lambiotte, Pontil, & Mascolo, 2012), detecting mobility behaviour for demand (Bayir, Demirbas, & Eagle, 2010), analysing the space-time variability in the population distribution in cities (Mobile Landscape Method in Ratti et al., 2006; Sevtsuk & Ratti, 2010); classifiying different "basic" profiles of city usages and consumption (Reades et al., 2007; Soto & Frías-Martínez, 2011). In this direction, big data represents one of the most promising sources for the analysis, visualization and interpretation of people's presence and movements in urban spaces and, in doing so, to orient policy making processes.

The second perspective concerns the valuable support offered by big data for "re-scaling" urban policy and assisting the construction of partnerships between different stakeholders, facilitating public participation processes. In this framework volunteered data (Goodchild, 2007), deriving from social networking activities and based on user-generated contents, working as enabling technologies, offer an effective support for urban mobility in two main ways:

- gathering *different types of information related to opinion mining and sentiment analysis* (Pang & Lee, 2008), on the quality and comfort of transport supply, on accidents or real-time problems on the networks that can be used by the Public Authorities to manage problems and improve transport supply;
- offering *strategic travel planning and communications scheduling* to facilitate the management of the daily micro-mobility, enabling people to rearrange trips more easily and avoid going back home or to their workplace between two activities.

Allowing a sort of "chance orchestration" (van den Akker, 2014), the use of mobile ICT will lead to a kind of 'optimization' of the trips people have planned during a day (Ling & Yttri, 2002). Trips can be optimized at both an individual and a collective level and thus contribute to sustainable mobility, especially in metropolitan areas (Janelle & Gillespie, 2004) and in public transport (Jain, 2006).

The combination of the ability to travel with the spread and use of mobile ICT could change the activity planning process and increase flexibility in daily life, for example through rescheduling on the move (Townsend, 2000). In this respect, some works (Aguiléra, Guillot, & Rallet, 2012, p. 668) suggest that it is not enough for individuals just to be informed in real time in order to be able to react to an unforeseen situation or a change, they need to be able to modify the activities they have planned and therefore have a degree of flexibility in their travel.

Despite the growing theoretical and operative interest in the potential impacts on behaviors, city morphologies and planning due to big data use in city (Guido, Rogano, Vitale, Astarita, & Festa, 2017) and mobility management, evaluations of practical experience suggest that such integration is prone, in concrete policy making fields, to specific limitations. Lim, Kim & Maglio (2018) underline the "lack of studies providing practical knowledge for real project to support a data-based smart city transformation". The same concept is shared by Semanjski, Bellens, Gautama &

Witlox, (2016) who suggest that the implementation of big data in decision making and planning process is still "an abstract idea" and that practical experiences "are still strongly service-oriented", with a prevalence of non-complementary bottom-up initiatives offering limited insights on the global impacts and roles of big data in medium and long-term planning perspectives. To fill this gap, this paper considers a sound policy cycle as the field of application of available big data so to understand, into an experimental perspective, how they can contribute to the whole formulation of a mobility policy process.

3. Big data in the urban policy cycle approach

The rich multiplicity of big data, even in relation to the sole field of urban mobility, needs to be related to its potential contributions to urban policy approaches. In our approach, we assume to work with a model based on the policy cycle that means conceiving policy as a process, by conceptualising it as a data assisted policy experimentation cycle, consisting of interrelated, stepwise or cyclical stages.

The 'experimental dimension' introduced in this approach helps to overpass some very known limitations recognised in the policy cycle framework, considered too simplistic in practice, and discrediting its assumption of policy as sequential in nature (Dorey, 2005; Hill, 2009, 143; Ryan, 1996).

As recognized by some authors (McFadgen 2013; McFadgen and Huitema, 2017), policy experiments form a useful policy tool to manage complex long-term policy issues by creating the conditions for 'ex-ante evaluation of policies' (Nair and Howlett, 2015): learning from policy experimentation is a promising way to approach 'wicked problems' characterised by knowledge gaps and contested understandings of future (McFadgen and Huitema, 2017). Based on the definition by European Parliament and Council (2013, art. 2 §6), policy experiment is any "*[…] policy intervention that offers innovative responses to social needs, implemented on a small scale and in conditions that enable their impact to be measured, prior to being repeated on a larger scale, if the results prove convincing*" (European Parliament and Council 2013, art. 2 §6). In this perspective, experiments generate learning outcomes, mainly made of relevant information in the process of policy making, under dynamic conditions (McFadgen 2013).

Considering the policy-cycle under the framework of the experimentation process, allows to focus on the governance design of policy making in which big and open data can be used, but also fertilized, thanks to the knowledge developed throughout the experiment carried out in the planning processes. The experimental dimension to embed new points of view in the context of the policy becomes crucial in policy design and policy implementation and makes the policy evaluation scope transversal to the other steps of the policy cycle, as well supportive of the other steps. This is the reason why we consider big data in relation with the different steps that compose a policy cycle, highlighting its possible uses, based on the experimental dimension we would like to implement. The contribution of big data changes according to the stages of the policy making process (fig. 1), which can be considered a recurring sequence of three main cycles: design, implementation, and evaluation

3.1. Policy design

The *policy design* cycle is focused on highlighting the existence of a collective problem, mobilizing a set of goals and objectives in relation to it, and defining policy strategies and actions as attempts to contribute to solving the problem. The phase of design, defining what is the intent that a policy instrument aims to achieve, identifies what procedure should be followed. In the field of urban mobility, policy-relevant problems refer to categories such as climate change, accessibility, health, safety, and congestion (Polivisu, 2018). Depending on how a problem is defined, different ends to be achieved and means to be used can be identified. This phase, strictly related to policy formulation phase, is directed towards the design of a policy instrument and contributes to the process of problem solving. In this sense, big data can provide a different contribution in each stage of a policy cycle, contributing also to significant processes of policy experimentation (fig. 1). Nonetheless, the main contribution of big data is the provision of evidence relevant for designing, implementing and evaluating policy measures (fig. 2). While big data can contribute to the range and quality of the available information, a clear definition of the problem to be faced is instead exclusively a result of the policy process and is necessary condition for addressing the policy formulation. In doing so, in the policy design cycle, problem setting and policy formulation are two inescapable phases.

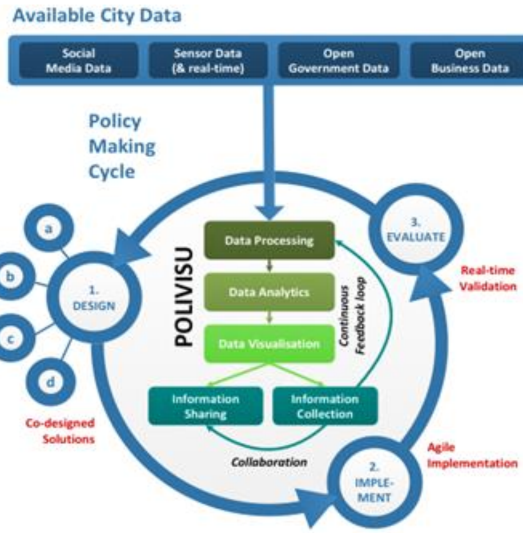

fig. 1 Data integration in the Policy Experimentation Cycle (https://www.polivisu.eu/)

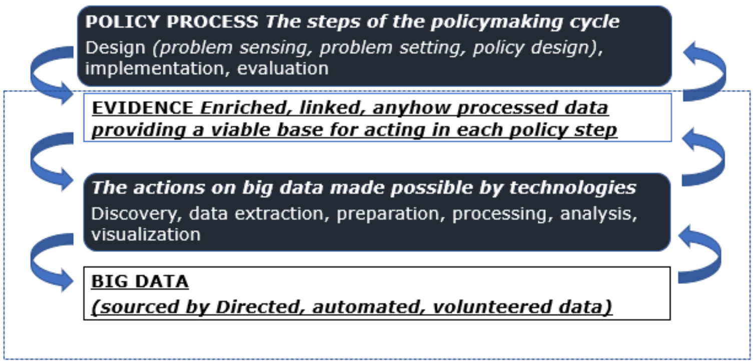

fig. 2 Data integration in the Policy Experimentation Cycle (https://www.polivisu.eu/)

3.1.1. Problem setting

In the policy cycle, problem setting highlights the existence of a collective problem to be faced, as well as legitimizing it as a collective problem; it consists of an analysis of the existing policy and how and if it deals with the problem and its implementation; and it is directed towards a reconstruction of the public debate about the problem, and the identification of the stakeholders and actors potentially involved.

In this step, data can be useful to explore the effectiveness of the past policies and to better know the current urban phenomena affecting the problem, depending on the issue that needs to be faced. The depiction of ongoing trends and the consequent definition of the problem to be addressed can be supported by the data collected through the real-time use of urban infrastructures and services. Among them, several kinds of traffic sensors to collect a large amount of data related to the movement of vehicles (Zhang et al., 2011), their speed and the occupancy of a road (Lu, Sun, & Qu, 2015), allow a real-time traffic flow state identification and prediction (Lv, Duan, Kang, Li, & Wang, 2014). Data mining proves useful also in the case of public transport, when smart cards are available to the users (Ma, Wu, Wang, Chen, & Liu, 2013) and provide elements for both long-term planning and real-time operations (Pelletier, Trépanier,

& Morency, 2011). Similar data are available also for different vehicle sharing systems, as for vehicles position and the information associated to each user.

Mobile phone traffic data is another crucial source, related to the position of each device connected to the cellular network (and, consequently, of the person who owns the device). Relevant contribution of these data refers to: positioning through location coordinates of mobile phones and the social identification of the people carrying, with the Social Positioning Method (Ahas & Mark, 2005; Ahas, Silm, et al., 2010, p. 5); time-space variability of population distribution in cities (Sevtsuk & Ratti, 2010); classification of urban spaces, according to mobile phone uses (Reades et al., 2007; Soto & Frías-Martínez, 2011); traffic monitoring tools (Bekhor, Toledo, & Prashker, 2008; Caceres, Wideberg, & Benitez, 2008; Fontaine & Smith, 2005). Mobile phone traffic data "offer multi-scalar maps to deal with the variability of the relationships, with time-dependent phenomena, with the heterogeneous rhythms of urban practices that are missing from traditional analysis, becoming a support for tracing fuzzy boundaries as perimeters of practices, useful for a "re-territorialization" of urban policies" (Manfredini, Pucci, & Tagliolato, 2016, p. 268).

Other data from social networking services (such as Facebook, Twitter, Instagram, WeChat and others) and based on user-generated contents are originated by the many interactions of users across such services, also in relation to urban issues (Kitchin, 2014a), providing information also on the position of the users, who may check-in when they are in a specific location (Liu, Sui, Kang, & Gao, 2014, p. 1). Such sources have a high degree of sensitivity to daily travel patterns, especially in densely inhabited areas (Chen & Schintler, 2015). Users may also report opinions and feelings about the travel experience (Casas & Delmelle, 2014; Pang & Lee, 2008), or (self)track their habits, performances and behaviours, (Jariyasunant et al., 2015, p. 111).

3.1.2. Policy formulation

In the policy cycle, policy formulation is directed towards the identification of shared objectives and the alternative options of intervention in relation to the problem emerged in the previous phase. The construction of scenarios can support the choice between different alternative options, assuming that the available options are alternative to each other and cannot be pursued at the same time. The alternatives are generated as possible options to deal with the emerged problem.

Given the strict relationship between the phase of problem setting, the available data are pretty much those already covered in that phase, while their possible use is different. In fact, the definition of alternative scenarios is one of the contributions of big data to the design of a policy instrument. Scenarios support decision making thanks to "the creation of alternative images of the future development of the external environment. In doing so, scenarios highlight crucial uncertainties, with impact on the (strategic) decisions managers have to make" (Postma & Liebl, 2005, p. 162). Therefore, scenarios support the choice between diverse ways of addressing a specific problem; in the field of urban mobility, scenarios may define alternative "transport futures" with different levels of possibility, plausibility and desirability (Banister & Hickman, 2013), going thus beyond the limited and yet prevalent 'predict-and-provide' approach (Goulden, Ryley, & Dingwall, 2014; Martens, 2006).

Scenario planning can use different methods to "create a set of the plausible futures" rather than "forecasting of the most probable future" (Amer, Daim, & Jetter, 2013, p. 25). Such different focus explains why scenarios are not interested in forecasting but rather in 'backcasting', that is, defining desirable futures and the action required to attain them (Dreborg, 1996). Big data can support the specific choice between alternative measures. Considering existing trends and possible future developments, as conveyed also by big data, it becomes possible to assess the potential benefits and costs of different hard and soft measures (Cairns et al., 2008). Interestingly, this estimation does not simply take into account the results achievable by a single measure, but can consider also some peculiar elements of policy, such as the packaging with other measures and the involvement of different stakeholders (Hickman, Ashiru, & Banister, 2010).

3.2. Policy implementation

In the stage of implementation, the policy defined in the previous stages is given form and effect, being put into practice and delivered to the public. The policy can originate different kind of actions, definable as incentives, norms and constraints, information, and infrastructure (Polivisu, 2018). In relation to these actions, data have a twofold role: they contribute to put the measures composing a policy into practice and to eventually reshape them. A policy in fact must take into account external conditions and adapt to their eventual change; it needs thus to be designed, in a process that takes time, provides occasions for learning and requires eventually to revisit the previous steps.

The contribution of big data to policy implementation consists of at least five dimensions: real-time management of infrastructures and services; tracking of changes in flows and consequent adaptations to them; provision of updated information; receival of feedbacks and overall participation of citizens in the delivery of services; availability of data to citizens and users.

Big data primarily provides elements for the real-time management of urban mobility issues, allowing a “much more sophisticated, wider-scale, finer-grained, real-time understanding and control of urbanity” (Kitchin, 2014b, p. 3). Such management refers to both specific sectors, both the whole city. Centralised forms of real-time management map phenomena and immediately plan operations immediately also thanks to big data (as in the famous Rio de Janeiro’s Centro de Operaçôes Prefeitura do Rio).

Experiences of ‘autonomous’ management may also emerge when subjects - external to institutions - develop their own forms of management and may impact the mobility of an urban setting. The experiences of two private companies, Waze and Citymapper, provide suitable examples of such private contributions. Waze, a GPS navigation software based on a participatory sensing system, collects information from the users and proposes alternative routing to the drivers; the app contributes thus to the management of urban traffic, but does so autonomously from the intervention of municipal institutions. Citymapper instead is a public transit map and mapping service, whose information is based on user-generated contents, open data and information collected by its employees; In May 2017, the company has launched in London a “smart bus service”, that is, a popup service whose routes “show up in A to B routing whenever the algorithm decides so based on their viability and frequency” (Citymapper, 2017) intended to be flexible and open to modifications that accommodate the changes of a city.

Up-to-date, complete and personalised information is another element to which big data can significantly contribute. A first application can improve the ‘info-structure’ related to specific transport modes, thanks to a strategic application of information technologies in the form of small, targeted interventions that complement other kinds of actions (Tomitsch & Haeusler, 2015). An improvement of the infostructure can be significant to show the available modal alternatives, provide updated information on the current service conditions, and even offer travel-related suggestions.

The uses of big data to provide information involve both public and private transport, from bus services (Falco et al., 2017) to parking facilities (Tasseron & Martens, 2017). Mobile applications available thanks to smartphones play a significant role too, providing complete information and producing potentially unforeseen consequences on the experience of physical mobility (Vecchio & Tricarico, 2019). The provided information may also be directed towards the promotion of specific sustainable mobility choices, fostering alternative behaviours in different ways (te Brömmelstroet, 2014): providing new, previously unavailable information (Anable, 2005); making visible the various economic and temporal costs associated with different travel options (Cairns et al., 2008); even offering rewards (Knockaert, Tsenga, Verhoef, & Rouwendal, 2012) or ‘gamifying’ (Kazhamiakin et al., 2015) personal mobility choices.

Big data can also contribute to the involvement of citizens in the implementation of policy measures. Apps and websites allow to receive feedbacks related to urban mobility issues, involving users in the co-design of a specific service (Kudo, 2016). Nonetheless, in this case citizens act mainly as consumers and providers of real-time information (Nunes, Galvão, & Cunha, 2014), for example through devoted consumer surveys (Ciasullo, Palumbo, & Troisi, 2017) that providing inputs for actions and measures which other subjects will design and implement.

Finally, even the visibility and availability of big data can be valuable in itself, thanks to the transparency they guarantee and the possible further uses that many subjects may make of them. Data in fact can be made accessible and visible to all citizens, as with urban dashboard websites that “produce visualisations that aid the interpretation and analysis, especially for non-expert users, and allow citizens to monitor the city for themselves and for their own ends” (Kitchin, 2014b, p. 7). Big data may be also made available to citizens who may make use of them, as in the Singapore

Live! project developed by the MIT SENSEable City Lab, which aims at "allowing developer communities to join in creating applications that turn these data streams into meaningful and beneficial tools for people to make use of in their cities" (Kloeckl, Senn, & Ratti, 2012, p. 90). Big data may contribute to a wider involvement of citizens also thanks to forms of "crowdsourcing" related to the public participation process for planning projects (Brabham, 2009). In relation to urban issues, this become the occasion for "harnessing collective intellect and creative solutions from networks of citizens in organized ways that serve the needs of planners" (Brabham, 2009, p. 257). However, the crowdsourcing of an urban problem can take place only "if a problem can be framed clearly, and if all the data pertaining to a problem can be made available" (Brabham, 2009, p. 252).

3.3. Policy evaluation

Policy evaluation analyses existing policies and their developments, considering the results achieved with the implementation process. Evaluation may take into account both desired and eventual undesired outcomes; it may examine how the policy contributed to address the initial problem, limiting damages or providing benefits; and it may consider how a policy may likely perform in the future. Moreover, an in-progress form of evaluation can accompany also the previous stages of a policy cycle, under the name of monitoring.

The main use of big data in relation with the evaluation of a policy is the appraisal of the adopted measures and the results they were able to achieve. Real-time data already conveys how a setting responds to the implementation of a given policy and can be useful already in the implementation phase. These may also be used in relation of indicators developed to assess the outcomes of a policy. In general, the definition of indicators proves to be a difficult task (Button, 2002), due to the manifold interactions between different factors and the different for defining indicators - a priori, crossing data, or even in a participatory way (Mameli & Marletto, 2014). However, evaluation does not simply arrive at the end of a policy cycle, but rather is being structured already when a policy problem is defined. The definition of the issue to be faced and of the objectives to be achieved already determine what indicators will be relevant for evaluation, what data will contribute to calculate them, and what procedures for data collection and evaluation will be established: evaluation does not simply refer to final results, but rather to the whole planning and implementation progress (Gühnemann, 2016).

Big data thus provide consistent elements for the evaluation of a policy, but again the information they offer needs to be selected in the light of the problem and the strategy pursued by the policy.

4. Citizens, policy and big data: Open issues

The availability of big data and its uses for policy purposes is currently limited. Significant datasets are often property of private companies from different sectors. Information is both a product of their operations and a condition required to access such services: "many digital services (are) offered for free, in exchange for our data" (Morozov, 2016), configuring them as 'big data companies' (Hirson, 2015) whose profits derive (also) by the sale of the wide and rich datasets they own. Nonetheless, even when they develop their own analytics tools, the ability to track and predict flows may be limited even when the main technological corporations are involved, as Google demonstrated in the recent past with its Google Flu initiative (Lazer, Kennedy, King, & Vespignani, 2011). The scattered ownership of big data seems in fact to be as significant as the technical limitations that characterise them, such as the limits of the predictability in human mobility (Song, Qu, Blumm, & Barabási, 2010) and the difficult replicability of big data experimentations, due to the continuous re-engineering of platforms (Lazer et al., 2011).

An apparent solution may be a higher involvement of private citizens in the production and the provision of data. Private citizens may act as 'sensors' (Goodchild, 2007) and become producers of data. Citizens are of course significant for most of the directed and automated data, being the subjects that are tracked by a number of fixed systems and portable devices; however, here it is significant to consider what are the data that they voluntarily provide as "gifts" (Kitchin, 2014, p. 4). Such data refer to mainly three categories: contents, tracks and cartographies. Contents include all the social media interactions, taking into account those remarks that may relate to urban mobility and may use also multimedia forms (for example, accompanying a personal status with a photograph or a video); where available, also the mobility-related warnings made through devices and platforms may refer to this group (for example, road holes pointed out to a municipal institution using a devoted app). Tracks instead refer to those habits and behaviours that people choose to record, as in the case of different sport practices (running, cycling…). Finally, people may also contribute to the creation of cartographic information using specific open mapping systems (Goodchild, 2007). The most aware of such contributions range thus from active forms of citizenship to examples of citizen science.

The production of data by citizens implies nonetheless different degrees of voluntarism and awareness, raising ethical issues that are still mainly unsolved. According to the three typologies of voluntary data previously mentioned, different is the role of individuals. Cartographies imply a contribution to data that are not personal, through individual knowledge and skills; in this sense, no sensitive information is involved in what may be a further manifestation of a specific 'hacker ethic' (Himanen, 2001) focused on improving life, enhancing access and guarantee freedom of information. Tracks instead voluntarily provide personal data, even sensitive one – for example, apps for sport practices involve routes but also individual physical information on age, weight, performances etc.; in this case, data are voluntarily offered in exchange of a precise log of personal activities, even if this allows detailed personal profiling. Contents in social media interaction instead contribute to the accurate reconstruction of individual profiles, not only in relation to mobility habits, but also to personal opinions: for example, a post on social media complaining about the traffic or the low quality of a public transport system may express also a complaint against the institutions running them; given the rich amount of data and the possibility for government to access them, inedited opportunities for surveillance and repression are provided to non-democratic regimes, in addition to the possibilities of control through the 'anomaly detection' already offered by manifold sensing systems (Difallah, Cudré-Mauroux, McKenna, 2013). Furthermore, some general privacy issues that involve automated and directed data refers also to volunteered data: the tracked subjects end up having "no place to hide" (Taylor, 2016) and may perceive to have a 'hindered freedom', due to the pervasiveness of tracking and surveillance systems (Sager, 2006). The volunteer provision of data by citizens is thus the result of a subtle trade-off between privacy and convenience, which undergoes continuous re-definitions.

Big data also suffer from incompleteness, an issue that questions the effectiveness of big data in representing urban phenomena. First, only some urban populations and their practices are conveyed by big data: portable technologies in fact are available only to some groups, due to the unavailability of portable devices or the lack of skills required to use them; as a consequence of such digital divide, also the deriving big data provide partial representations of urban phenomena (Graham, 2011). Also, mobility practices not grasped by big data, or latent demand for mobility currently unable to express itself, may remain invisible and be consequently ignored in mainstream urban mobility planning approaches. These in fact tend to plan according to demand predictions (Martens, 2006), so that "consumers do not escape the constraining *have to* if they want to enjoy the freedom of *having the opportunity* to. They have to make a lot of trips in order to be mobile – even in the sense of being *potentially* able to travel" (Sager, 2006, p. 472). Such limitations originate omissions in the representation of urban phenomena and exclusion of 'data-invisible' populations, giving to big data a 'marginalizing power' (Kwan, 2016) that questions their fairness as well as their policy usability.

5. Conclusions

The paper has explored how big data can innovate urban policy by focusing on the field of urban mobility and on the experimental dimension of policy.

Big data is increasingly seen as a source of knowledge that is relevant not just for its size, but also for the unprecedented operational opportunities it provides. Big data related to urban mobility phenomena are spatially and temporally extensive and detailed, contributing to an enhanced understanding of urban phenomena. A first use refers to understanding urban phenomena considering big data in themselves. Crucial in this sense are geovisualisation and geovisual analytics, somehow a consequence of the development of GIS techniques. Emerging data can provide the basis for interpreting specific urban phenomena, for example detecting specific mobility patterns and defining accordingly different mobility profiles (Bayir, Demirbas, & Eagle, 2010), and to predict behaviours, for example thanks to the recognition of 'universal patterns in human urban mobility' (Noulas, Scellato, Lambiotte, Pontil, & Mascolo, 2012). A second use refers instead to the interaction with other knowledge sources, for both interpretative and operational uses. Big data may interact with more traditional sources, such as census data and land use, to provide the basis for comparisons and deeper understanding of urban phenomena (Manfredini et al., 2016, p. 255) and for improving established interpretative models for urban mobility, as with accessibility measures (van Wee, 2013).

While the heuristic relevance of big data is increasingly investigated, the contribution of this new knowledge source to policy processes requires deeper analysis. Right now, techno-enthusiast discourses celebrate a generic future smart urban mobility but do not recognize the issues raised by need of defining urban mobility problems and consequently determine possible policy answers. While acknowledging the impossibility of simply relying on (big) data for framing urban mobility problems and possible solutions to them, and considering the potential disruptions brought by big data into the transport planning practice, probably the observation of real-world cases can provide crucial elements for considering the relevance of big data for policy. Focusing on policy processes where data were used, rather than simply focusing on technological solutions fostered by big data, can provide unprecedented insights on the policy contribution of data. In this sense, relevant can be the ongoing work of the Polivisu H2020 project, in which three mid-sized European cities are acting as pilot cases using big (open) data visualizations in relation to different urban mobility issues. However, for now a critical reflection on big data can be significant for determining the relevant categories through which examine ongoing policy processes and design future ones.

Our overview of the academic debate, strengthened by the references to different ongoing experiences, has highlighted how relevant is to acknowledge the multiplicity of big data in order to exploit its contribution to effective urban policies. Such multiplicity can be observed in relation to at least three aspects: first, the different sources and knowledge that big data provide; second, the different roles that data may have in the different stages of a policy cycle; third, the many actors who are involved not simply in policy issues, but also in the very production, storage and management of big data. These aspects are fundamental for defining how big data can intervene at different stages of a policy cycle and, consequently, help design an effective model for innovating urban policy. In this sense, it is necessary to move the emphasis from the technological tools required to take advantage of big data to their many possible uses in relation to policy issues.

Acknowledgments

The authors acknowledge the funding received from the European Union's Horizon 2020 research and innovation programme under grant agreement No 769608 "Policy Development based on Advanced Geospatial Data Analytics and Visualisation". Polivisu Project H2020 -SC6-CO-CREATION-2016-2017.

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