An Urban Data Business Model Framework for Identifying Value Capture in the Smart City: The Case of OrganiCity

Shane McLoughlin, Giovanni Maccani, Abhinay Puvvala, and Brian Donnellan

Abstract Governments' objective to transition to "smart cities" heralds new possibilities for urban data business models to sustain and scale urban data-driven solutions that address pressing city challenges and digital transformation imperatives. Urban data business models are not well understood due to such factors as the maturity of the market and limited existing research within this domain. Understanding the barriers and challenges in urban data business model development as well as the types of opportunities in the ecosystem is essential for researchers as well as practitioners from incumbents to new entrants. Therefore, this chapter introduces a framework for understanding and classifying urban data business models (UDBM). We furthermore illustrate the application of this framework to a heterogeneous sample of emerging smart city solutions. An embedded case study method was used to derive the framework by analyzing 40 publicly funded and supported urban data focused experiments that address pressing city challenges under the H2020 OrganiCity initiative. This research contributes to the scholarly discourse on business model innovation within the context of smart cities.

Keywords Organicity · Smart city case study · Urban data business model · City values · Value creation

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Introduction

The paradigm of "smart cities" as a response to increasing urban population, environmental pressures, budgetary restraints, legacy IT systems, ongoing city developments, and renewal, as well as policy and rationales for citizen participation and engagement, has opened up new possibilities for urban data focused solutions (supported by viable business models) as responses to pressing city challenges and digital transformation imperatives (Loebbecke & Picot, 2015). Here, we refer to "urban" as "relating to a town or city" (Oxford English Dictionary, 2017) and business model as the value creation logic of an organization (Osterwalder & Pigneur, 2010). Reviewing existing definitions of "urban data" (Wolff, Kortuem, & Cavero, 2015) and "urban big data" (Pan, Tian, Liu, Gu, & Hua, 2016), we define urban data as, *data concerning one or more town or city spatial region(s) physical, social, cultural, political, or economic environment*. Thus, urban data is about a town or city region(s) citizens, its infrastructure, its businesses, government, and natural environment, etc. For example, "Citymapper" acquires and exploits urban data to offer citizens the value of improved wayfinding across several European cities (Citymapper, 2019). Citymapper leverages such sources of data as citizens' geolocation, their intended destination and open urban transport data to offer its mobile app-based solution for delivering improved wayfinding. Whilst open data, citizens' smartphones and the technology behind Citymapper's app serve to enable such wayfinding, it is the business model encompassing the necessary resources, competencies, activities, and partners, etc. that sustainably delivers the solution to citizens, i.e., making Citymapper economically viable to sustain and scale.

In recent years, business activity has focused on developing pilots, demonstrating prototypes with some offering commercial solutions to cities. However, the sustaining and scaling of an ecosystem of urban data business models (UDBM) has proved slow and in some cases fraught with difficultly. Compared to previous data-driven business models (e.g., through open data from the public (Zuiderwijk & Janssen, 2015) or private (Lakomaa & Kallberg, 2013) sector or other data marketplaces), the context of urban data heralds specific technical, sociopolitical, ethical, and economic challenges, etc. Urban data may be existing data that can be purchased, reused for free or even generated through development of sensing technology or crowdsourcing initiatives. These processes create value networks comprising of different actors (Tammisto & Lindman, 2012) which significantly add complexity to business model creation (Janssen, Charalabidis, & Zuiderwijk, 2012) (Hofman, 2015). Data-Driven Urbanism (Kitchin, 2016) or "Datafication" (Maull, Godsiff, & Mulligan, 2014) of urban life therefore needs to overcome additional challenges.

Overall, digital transformation oriented around data and digital technologies (such as IoT, (web) software, cloud, AI-based analytics) is enabling service/process/product innovation, including the very processes and outcomes for achieving those innovations (OECD, 2019). As "data" becomes seen as the "new oil" and a critical source of new insight for cities, policy translating to research efforts in the EU has focused on developing a marketplace and supporting social innovation through various capacity building exercises such as policy and funding for incubators, R&D, and experimentation. Thus, the EU is playing a central role in promoting, fostering, and facilitating economic development and new business creation, centered around creating value from urban (big) data supported by digital technology innovation. Some of the most popular examples include federated Living Lab flavored initiatives like OrganiCity (Organicity, 2018) and SBIR (Small Business Innovation research) pre-commercial procurement mechanisms to support and promote (collaborative) innovation, such as among entities, sectors, businesses, and across cities themselves (Gutiérrez et al., 2016). In this regard, Governmental funding and support to "market make" new urban data ecosystems by funding research to address standards, interoperability, and encourage experimentation for innovation may lead to exponential growth of an ecosystem of innovative value propositions. In this regard, commercial vendors and social enterprises have struggled in developing sustainable business models due to continuing lags in standards, interoperability, data models, IoT (Internet of Things) and telecommunication network cost, capability, and maturity, as well as ethical concerns and budgetary constraints by cities, etc. By ameliorating roadblocks of technological standards and data models (e.g., Fireware) as well as barriers to experimentation, etc. it is hoped that a critical mass of differing urban data types and sources will unlock new opportunities for UDBM by establishing network synergy in an urban data ecosystem. "Scaling" is a crucial factor in realizing these opportunities as a minimum viable business case for a vendor could depend on multi-city/country take-up of an offering. In this regard, multi-city and multi-country experimentation by vendors is needed to develop solutions compatible across differing political–cultural–environmental–social contexts.

Finally, despite academic debate on how to conceptualize business models, there is agreement that business models articulate value creation (Hossain, 2017) communicated and delivered to customers as the "value proposition," i.e., the product or service experienced by customers. Within the recent academic literature, there have been some efforts at formulating data business model dimensions, classifications or taxonomies of: data-driven digital services (Rizk, Bergvall-Kåreborn, & Elragal, 2018), concept definitions across the data value chain (Curry, 2016), business models for open data (Ahmadi Zeleti, Ojo, & Curry, 2014), and data-driven business models (Engelbrecht, Gerlach, & Widjaja, 2016; Hartmann, Zaki, Feldmann, & Neely, 2016). However, no study has developed a framework that can apply a consistent language and lens to organizations focusing on urban data solutions. Such a framework can be fruitful for researchers as an analytical lens in (1) identifying and understanding challenges across the value network in developing UDBM, (2) identifying opportunities for new value propositions and related UDBM combinations, and (3) substantiating commercially successful types of UDBM out there. Thus, we pose the following research question:

RQ: What are the related value generating elements that inform differentiated value propositions and related urban data business models?

To address the research question, we carried out a case study the EU H2020 project OrganiCity (EU, 2017) and 40 of the experimental solutions it has funded and supported, in order to derive an urban data business model (UDBM) framework. These experiments are addressing city prescribed urban challenges, in developing innovative solutions and related UDBM, with an approach that emphasizes open innovation, co-creation, and real-world (and in some cases multi-city) experimentation methods.

The remainder of this chapter is organized as follows: Section "Related Work" overviews the related literature on business models, business model experimentation and existing frameworks, and taxonomies of data-driven business models. Section "Methodology" describes the method including the case and sample. Section "Validated Framework" describes the validated framework derived from the case study. Section "Application of the Framework" illustrates the application of the framework in characterising heterogeneous clusters of cases from OrganiCity. Finally, Section "Conclusion and Future Work" concludes by comparing the framework to existing work and identifying future research work.

Related Work

Despite the clamor for technological innovation in most advanced societies, it is often the particular business model innovation tied with the technological artifact that yields value to the innovator and the society at large. For example, Dell's business model revolutionized computer sales in the 1990s with its direct to consumer approach. Dell's business model innovation centered on "made to order" and "direct to consumer" computer sales, supported by an e-commerce strategy. The approach helped to ensure Dell-brought technological advancements in computer parts quickest to market, whilst eliminating the cost burden of storage and unsold inventory. Thus, consumers could access the latest technological innovations at a competitive price. A business model is an expression of the particular value creation logic of an organization (Osterwalder & Pigneur, 2010) in delivering value, both to the customer and the organization. In the case of Dell, their value creation logic centered on the resources and capabilities needed to implement a robust e-commerce strategy and business process reengineering of the assembly and logistics process in order to: eliminate inventory, reduce third-party retail venders, and bring technological advancements quick to market. Thus, a good business model is essential to ensure value for the company and the customer, differentiate the organisations approach from it's competitors, and give a company competitive advantage.

To identify and understand business models, Osterwalder and Pigneur (2005) defined a business model as a "conceptual tool that contains a set of elements and their relationships." These elements or key dimensions of business commonly include: the resources, capabilities and activities needed to capture value and deliver the product or service (the value proposition); the cost structure and revenue stream and the needed partners beyond its organizational boundary, as well as the customer relationship and channels of interaction. The characteristics of these key elements and their relationship for a particular organization are strongly influenced by the values and mission of the organization and its external environment including: the customer, the competitive environment, government policies and regulations, economic conditions, and available resources, etc. However, business model elements are static and often fail to give a sense of firms in action.

The dynamic perspective is key to identify an organizations journey towards establishing a sustainable competitive advantage. However, the two widely accepted views—industry positioning view and dynamic capability view discuss the conditions for competitive advantage but do not elaborate on the journey towards it (McGrath, 2010). The industry positioning view proposes a truly differentiated position within an economic environment that can be defended to achieve competitive advantage (Porter, 1991). The dynamic capability view argues that such an advantage can only be attained by developing competencies or capabilities that are hard to replicate by others (Teece, 2007). Moreover, McGrath (McGrath, 2010) argues that business model innovation for attaining competitive advantage can be strictly categorized neither as a positional approach nor as a capabilities approach. In a fast dynamic setting of technology-based businesses, it is often impossible to visualize factors and constraints that eventually prove to be competitively important at the time that decisions pertaining to business model innovation need to be made. In such cases, experimentation is the preferred strategists' tool of choice over analysis. In addition, business models' evolution is path dependent—early experiments and/or decisions often shape the future business model (McGrath, 2010).

We also draw from the business ecosystems' literature for this study. The ever-growing interconnectedness associated with the networked economy prompted the research community to refocus on business ecosystems (Moore, 1993). Moore (1993) explains business ecosystems as an allegory of natural ecosystems in order to present the way companies should do business together. Ecosystems comprise of multiple actors working together that contribute to the ecosystem's core purpose despite having seemingly unrelated value propositions. Hence, the business ecosystem view includes a network of actors unlike that of a conventional value chain view which focuses on delivering a single value proposition to the end customer (Baghbadorani & Harandi, 2012). From an ecosystem point of view, we next review frameworks that map actors of business ecosystems that are closely connected to the urban data ecosystem. Table 1 has a snapshot of related studies in domains where data plays a vital role.

Hartmann et al. (2016) framework deals with data-driven business models. Their study defines data-driven business models as the businesses with data as a key resource. Though, Hartmann et al. (2016) acknowledge that this criterion used for determining whether a business model is data-driven or not is ambiguous, given the ubiquitous importance of data to all the business models. Moreover, despite the use of multiple case studies to cluster business models, the framework development lacks inductive case study-based reasoning to develop the framework insofar as the design was based on a review of existing literature. Moreover, the framework's characterization of various second order elements leave scope for redundancies which in turn translate in to multicollinearities between explanatory variables during cluster analysis. Hartmann et al. (2016) have developed a similar taxonomy for

Table 1 Related studies

Authors	Methodology	Research Question	Domain
Hartmann et al. (2016)	Deductive study from existing BM literature	(1) Framework to analyse and compare DDBMs (2) Taxonomy of data driven business models	Data driven business models
Engelbrecht et al. (2016)	Combination of deductive and inductive approaches	To identify the dimensions of data driven business model to develop a taxonomy	Data driven business models
Schmidt, Drews, and Schirmer (2018)	Inductive study	To develop a taxonomy of Fintech business models	Fintech business models
Rizk et al. (2018)	Combination of deductive and inductive approaches	(1) What characterizes data driven digital services? (2) How can data driven digital services be clustered?	Data services
Turber, Vom Brocke, Gassmann, and Fleisch (2014)	Design science research	To develop a framework that captures specifics of IoT driven ecosystems	IoT business models

Fintech business models. However, their study used Hartmann's (Hartmann et al., 2016) framework for representing 195 Fintech business models that were further clustered to derive six clusters, when put together represent the Fintech ecosystem.

Turber et al. (2014) proposed a framework to map IoT business models on to a 3D space with dimensions representing the who, where, and why of a business model. Whilst the study represents an interesting way of mapping value creation across the ecosystem, it does not focus on capturing various intricacies associated with value creation, capture, configuration, and delivery.

Engelbrecht et al. (2016) too map data-driven business models on to a three-dimensional decision tree. The three dimensions (1) data source (user/non-user), (2) target audience (consumer/organization), and (3) technological effort (high/low) derived from a study involving "expert interviews." The decision tree is used to map 33 data-driven business models into eight categories. Like Hartmann et al. (2016), Engelbrecht et al.'s (2016) work helps us to identify the higher order dimensions central to a data-driven business model. However, unlike Hartmann et al. (2016), Engelbrecht et al. (2016) do not represent the granularity of sub-dimensions composing data-driven business models. Final, Rizk et al. (2018) study on data services focuses on service interactions between customers and service providers. The study focuses on the key activities necessary to understand data-driven digital services, as "Data Acquisition," "Data Exploitation," "Insights Utilization," and "Service Interaction" (Rizk et al., 2018).

Based on the review of related literature, we have identified the higher order dimensions of an urban data business model with which to investigate cases to derive a framework. Although various business model ontologies (Osterwalder & Pigneur, 2005), matrices (Walravens & Ballon, 2013), etc. identify various dimensions of a business model, we follow Hartmann et al. (2016) approach (which has been utilized by IS researchers (Schmidt et al., 2018)) by focusing on the most commonly cited dimensions of a business model (Hartmann et al., 2016). Hence, the higher level dimensions of the framework to explore consist of: “Key Resources,” “Key Activities,” “Target Customer,” “Revenue Model,” “Value Proposition,” and “Cost Structure.”

We have adopted a value proposition focused definition for the business models empirically examined for this study. For instance, a company that produces sensors to measure urban data may not qualify unless they include data management services in their offering portfolio. Thus, we define an urban data business model as a business model where urban data is central to the value proposition. This implicitly means urban data is a key resource.

Methodology

Research Design

In the UDBM context, given its nature, we argue the conventional dichotomy between the social and the technical is problematic as technical and social choices are constantly negotiated and socially constructed (Bloomfield & Vurdubakis, 1994). Therefore, also given the exploratory nature of this study, an interpretivist approach has been chosen as the primary means for addressing the RQ (Walsham, 1993). From an ontological perspective, this means that we investigate UDBM development as a complex phenomenon that is contingent on several social actors and activities. In order to capture this richness, inductive qualitative interpretive case study method was found to be suitable (Eisenhardt, Graebner, Huberman, & Miles, 2007).

Although there are numerous definitions of case studies, Yin (2003) defines the scope of a case study as follows: “a case study is an empirical inquiry that (1) investigates a contemporary phenomenon within its real-life context, especially when (2) the boundaries between phenomenon and context are not clearly evident” (Yin, 2003). Hence, case study research is a qualitative approach in which the investigator explores a bounded system (a case in a specific setting/context) over time, through detailed in-depth data collection (Orlikowski & Baroudi, 1991). A “holistic” case study is shaped by a qualitative approach focusing on a single unit of analysis, whereby an “embedded” case study involves subunits of analysis which focus on different salient aspects or levels of the case. These subunits are specific and relevant aspects for answering the overall research questions (Yin, 2003). Analysis of each subunit is completed “within-level” before “between-level” analysis occurs (Yin, 2003).

Inductive qualitative case study researchers usually combine multiple data collection methods (Yin, 2003) and keep the data collection and analysis processes flexible. Multiple sources of data were leveraged to “provide stronger substantiation of constructs" (Eisenhardt, 1989), i.e., the elements of the framework. In interpretive IS case studies, as an outside observer, Walsham (Walsham, 1995) argues that interviews are the primary data source, "since it is through this method that the researcher can best access the interpretations that participants have regarding the actions and events which have or are taking place, and the views and aspirations of themselves and other participants" (Walsham, 1995). Figure 1 below illustrates the stages of our approach. Data was thematically coded, by grouping common characteristics in relation to value creation of cases examined. We carried this out in iterative steps until all 40 cases were examined, and referred back to existing literature to best define and draw from prior literature in naming these sub-dimensions upon completion.

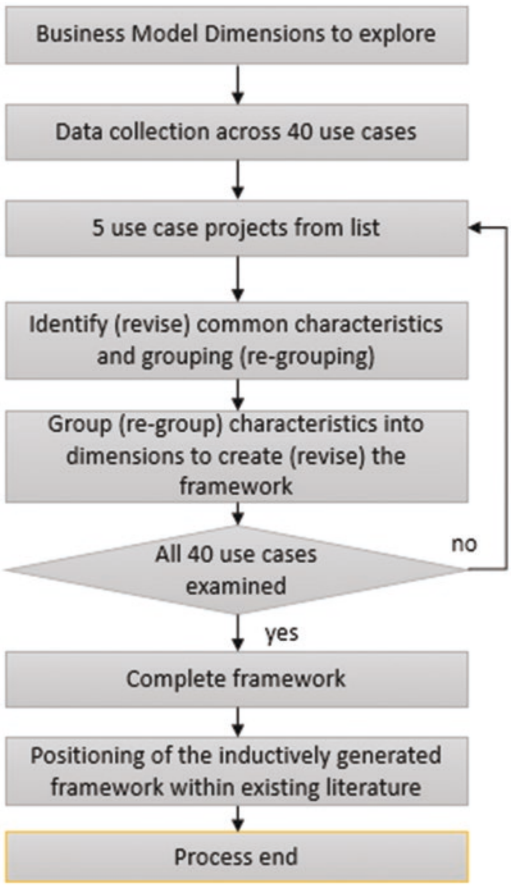

Fig. 1 Process of UDBM Framework development

Case

OrganiCity is a cross-European funding and support mechanism (including methodological guidance and IT capabilities) for experimentation of innovative urban data-driven solutions that address pressing city challenges. Originating as a H2020 research project with funding and development between 2015 and 2018, its model is an "Experimentation as a Service" (EaaS) facility. It can in some respects be envisioned as a type of federated "Living Lab" infrastructure across several European cities (e.g., London, Santander, and Aarhus) with the goal of enabling and supporting innovative urban data solutions ranging from environmental pollution monitoring to new forms of citizen engagement, etc. OrganiCity works with cities in defining city challenges to fund, with a core principle of "Co-creation" and "Real World Experimentation" in funding and supporting the defining of problems and reaching solutions. The rationale for its federated multi-city support and "Living Lab" flavored principles is to encourage the sustainability and scalability of the solutions emerging. Furthermore, it supports experimenters with a "toolkit" of both IT capabilities (centered and the OC digital platform) that can aid experimentation and privacy, ethical, and methodological guidance in carrying out experiments (see Table 2 for an overview of core features and rationale).

Between 2016 and 2018, OrganiCity organized two open calls to fund and support over 40 European "experimenters" ranging from start-ups, SMEs to grassroots movements in ideating and developing prototypes that acquire and leverage urban data to deliver a urban data-driven ecosystem, thus contributing to realizing the "smart city." Many of these experiments developed or leveraged sensor or human interface-based Internet of Things devices (IoT), mobile or web-based apps, social media, and open government data.

The first funding call was open to individuals, associations, organizations, or businesses and awarded funding of up to 60,000 euros to experiment as well as supportive guidance and resources. Evaluation of proposals for "experimentation" was by the "OrganiCity Experiment Evaluation Committee (EEC)." This committee consisted of two external experts, an OrganiCity Technical team member and one representative for each of the original cluster cities (i.e., Aarhus, London, and Santander). Proposals in both open calls were evaluated in terms of the novelty,

Table 2 Key organicity features and their rationale for sustaining and scaling

Features	Rationale for sustaining and scaling
Federation	Solutions address common challenges across European cities
Real world experimentation and co-creation	Solutions work in real world environments, and are more fit for purpose from co-creation with end-users and insight from various stakeholders
IT capabilities	Reduce time and resource barriers to prototyping
Funding and guidance	Reduce barriers to experiment and increase competencies for solution development
Brand and community	Promote credibility and synergies for and amongst experimenters

impact, and feasibility of the idea, with additional criteria of sustainability in the second open call. Furthermore, Co-creation was expected as core pillar of the experimentation design. "Experimentation" was understood in terms of planning, staffing, co-creation activities, testing, prototyping and evaluation, and reporting. Each experiment group had an appointed experiment lead, who coordinated the group and was responsible for providing feedback to OrganiCity (EU, 2017).

Data Collection

In case studying OrganiCity, we collected and analyzed various documents, reports, blogs, and publicly available information from 40 OrganiCity funded experimenters, as well as OrganiCity documents and city policy strategies. Furthermore, we analyzed in-depth interviews that took place with 30 of the 40 experimenter teams. Additionally, we interviewed city stakeholders across London ($N = 8$). The combination of this data helped us to understand both (1) OrganiCity and (2) the ecosystem of experimenters and their journey towards developing solutions. The data collected and thematically analyzed contributes to our understanding of a European urban data ecosystem and the development of urban data business models.

Upon initial analysis of the experimental cases, we identified 27 of the 40 experimenters were SME/start-ups and the rest related to NGOs, grassroots initiatives, academic projects, or multi-stakeholder partnerships. We included all cases as they could offer us insights into the data resources being leveraged, the technologies being developed and the key activities undertaken to deliver solutions. Furthermore, although some of the experiments were not-for-profit social innovation-focused organizations, they still wished to sustain the solution.

Over half of the cases (52%) related to environmental solutions (i.e., education, air quality, vegetation, sound, water, waste, and health), 12% social welfare (housing, security, disabled, and health), 12% multi-domain, 10% mobility (parking, wayfinding, and carpooling), 5% tourism, 3% urban planning, 3% Government procurement, and 3% sport. Forty-three percent had an IoT-based experimental element (most of these sensor based), whilst the remainder concerned mobile apps, web platforms, data, or innovation in hardware-based data interaction. Many relied on APIs, whilst some drew on social media platforms.

Validated Framework

In this section, we describe the validated framework derived from an analysis of the cases. We use examples from the variety of cases where necessary to illustrate inclusion of the sub-dimensions or elements, though this has been restrained due to the need for brevity. Details of all the cases can be accessed through the OrganiCity website at www.organicity.eu (EU, 2017). The framework is presented in Fig. 2.

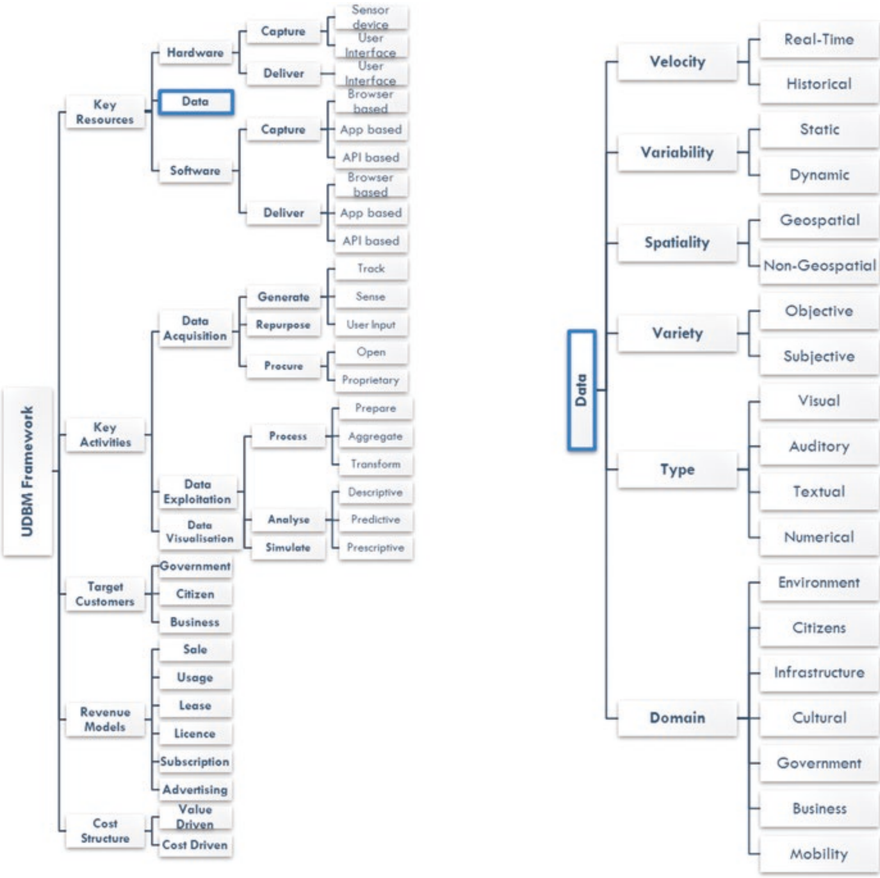

Fig. 2 Urban data business model framework

further below. What follows is a description of its dimensions and sub-dimensions, with the aid of examples where possible to aid concept definitions. Through applying the method for deriving the framework, we determined that "value proposition" will logically flow from other higher level dimensions of the framework, and thus was not included in the final framework. It should be noted that we chose to omit from the framework common elements (for example, data management and security, storage…) across cases examined that do not clearly identify value-adding elements that differentiate UDBMs.

Key Resources

Data

In terms of "Key Resources," both Engelbrecht et al. (2016) and Hartmann et al. (2016) distinguish "Data Sources" as the "Key Resource." For Hartmann et al. (2016), this is classified as "internal" and "external" data, whereby "internal" data concerns data generated through crowdsourcing, sensing or tracking, or existing sources of internal data repurposed to deliver the value proposition. "External" data is data acquired externally and further differentiated by such factors as "freely available" data, "customer provided" data, "web tracked" data, "open data," or "social media" data. On the other hand, Engelbrecht et al. (2016) differentiated data source as "User data" and "Non-User Data." However, we argue that sourcing the data is a key activity and not a key resource, whereby Hartmann et al. (2016) already captures "Data Generation" and "Data Acquisition" as an activity. Instead, we argue "Data" as the "Key Resource" should focus on the nature of the data the company generates, repurposes, or procures through various activities. The nature of the data as a key resource can then be looked at in terms of its characteristics for delivering the value proposition. For example, open data comprising of real-time geospatial pollution data may be procured from the city and overlaid with geospatial mobility data generated by IoT sensors, in order to deliver descriptive insights about the relationship between traffic and pollution.

Importantly, the characteristics of the data have a bearing on such aspects as the resources and capabilities needed to leverage the data, as well as wider socio-political factors on its collection and use. For example, generating real-time data may require greater storage, could have higher telecommunication costs, additional processing and analyzing capability and may not be suitable to generate through low powered sensor devices. Auditory or visual data may involve additional privacy and security considerations, whilst open data may have sustainability concerns if a business is reliant on data's updating and longevity (Maccani, Donnellan, & Helfert, 2015). In all we found data could be characterized according to "velocity," whether "real-time" streaming data or near "real-time" data (data sensed and uploaded very frequently), and "historical" data, i.e., all other data. For example, several experiments provided near "real-time" data by using low powered sensors, rather than "real-time" streaming. The "variability" of data was also a consideration, whereby "static" data refers to data unlikely to change over time. For example, data on the location of assets in the city. "Variability" also relates to "dynamic" data, which is data that is likely to change and thus requires frequent measurement. For example, Spend network drew on both "static" and "dynamic" open data to offer insights into city councils. Data may also have "variety" in term of being "subjective" or "objective." "Subjective" data refers to "user-input" based data such as with the case of "Tranquil City" where citizens identified tranquil spaces in the city, or "objective" data such as "iCycle" (IoTee Lab) which use IoT to measure the fill levels of bottle banks. The type of data, "Auditory," "Textual," "Visual," or "Numerical," was also an important distinction in the proposed solution offered, and the resources and activities needed to capture the data and deliver the solution. For example, citizens "textual" annotation of IoT-sensed "numerical" data is used by "Camon" to aggregate "objective" and "subjective" air quality levels.

Finally, we distinguish the "Domain" of urban data in terms of "Environment," "Citizens," "Cultural," "Business," "Mobility," "Infrastructure," and "Government." For example, "Infrastructure" data relates to urban spaces and places and facilities in the city including buildings, parks, power supplies. This may relate to unused or vacant spaces in the city, such as is the solution from the social enterprise, "Space Engagers." "Environmental" data refers to data about the natural environment of the city such as air and water, wildlife, or even soil and grass such as the case of experimenters "Green Roof Monitoring." "Citizens" data refers to any data about citizens, often communicated by citizens. For example, "Data on Site" proposes new ways for citizens to interact and submit data about the city. "Government" data relates to data about city governance and council activities and processes, as was the case for "Spend Network" who drew on open data to offer insight into public sector sending. "Cultural" data refers to data about history, events, social activities, etc. in the city, such as for "Walks in the City" developed a map to recommend places and spaces' for senior walkers. Finally, "Mobility" relates to traffic, travel and wayfinding-related data in the urban context. For example, "Traffic controlled by air quality," which aimed to improve movement of traffic to improve air quality levels.

Hardware and Software

Not only will the nature of data needed to deliver the value proposition have implications for resources and activities of an organization, but the hardware and software resources suggest the type of value proposition an organization offers, whether in capturing data and delivering data or insights. We found these differed across cases examined warranting the inclusion of these sub-dimensions. For example, to offer a city and its citizens "Sensing as a Service" of real-time air pollution levels, an organization may require: (1) installing IoT (Internet of Things) "hardware" "sensors" on assets across the city in order to "capture" data, (2) a "hardware" "user interface" combined with "app-based" "software" installed in public places in order to "deliver" "descriptive" insights to citizens, and (3) "browser-based" "software" in order to "deliver" "predictive" insights to city officials.

Thus, we further differentiate "Key Resources" in terms of "hardware" and "software" specifically needed to "capture" data and "deliver" data and/or insights through the value proposition, though acknowledging that hardware and software resources needed by organizations go beyond these value-adding elements. Engelbrecht et al. (2016) identify "technological effort required" in distinguishing data-driven business models, this study proposes both "Key Resources" (in terms of hardware and software) and Key Activities (e.g., preparing data to prescriptive insights and visualization) and elucidates technological effort in how urban data business models are identified. Therefore, in terms of hardware, a "sensor device" such as an IoT device may be used to capture "objective" noise levels across the city, such as with the Belgium organization, "Sensifai." A "user interface" may be installed for the public to capture "subjective" views of sound levels by citizens, and then aggregated, analyzed, and visualized in delivering prescriptive recommendations to city officials through a hardware "user interface," and delivered to citizens through an "app-based" mobile software program. For example, "Research X Design" (Data on Site) developed a toolkit solution for public participation, whereby voting hardware and software devices are installed on city assets. "Empati" designed mobile flower pot style interfaces to place in city parks to gather subjective feelings of citizens.

Key Activities

Following Rizk et al. (2018), we propose that "Data Acquisition" is a key activity whereby an organization draws on: (1) hardware and/or software resources such as sensors, trackers, or "user input" interfaces to "generate" data, (2) software resources including APIs to "procure" either "open" or "proprietary" data, and/or (3) existing data resources internal to the organization, i.e., "Repurpose." In terms of "sense," we refer to Internet of Things (IoT) devices installed in a town/city, or data captured by sensors on a citizen's smartphone, e.g., GPS. By "Trackers," we refer to algorithms and cookies that allow an organization to capture web-based data such as social media data or website data including user online activities. By "user input," we refer to data entered by citizens through an interface device such as voice or text. We further distinguish, "Data Exploitation" (Rizk et al., 2018) and "Data Visualization" as sub-dimensions of "Key Activities." "Data Exploitation" aims to create additional value from the data through "processing," "analyzing," and "simulating" data. By "processing" we mean "preparing" (cleaning, structuring, etc.), "aggregating" (combining datasets or different types of datasets), and/or "transforming"(converting or modifying) data (Fayyad, Piatetsky-Shapiro, & Smyth, 1996), which is a lower degree of data exploitation and abstraction. "Analysis" and "Simulation" are a higher level of "Data Exploitation" aiming at extracting knowledge, i.e., insights (Rizk et al., 2018). These can be classified as "descriptive" (summarize or report patterns and relationships), "predictive" (analyzes data to make "predictive descriptions" or "predictive foresight"), or "prescriptive" (identifies options, suggests or recommends actions) insights (Hartmann et al., 2016). In terms of "predictive" analysis, we observed experiments which leverage AI and NLP (National Language Processing) to predict the characteristics of data, i.e., what we term "predictive description." For example, predicting with high probability that a sound belongs to a species of bird, or an image contains a certain number of people. This level of data exploitation exceeds that of descriptive analysis using more traditional methods. "Predictive foresight" on the other hand refers to predicting future states/events. For example, predicting cost savings, when bins will become full, or when additional policing resources will be needed. “Simulation” refers to the recreation of a complex system to run various “what if” scenarios and assess the possible behaviors of an actual system. In the context of digital innovation, virtual modeling, or simulation is becoming an ever more attractive value proposition (OECD, 2019).

Finally, “Data Visualization” (Elgendy & Elragal, 2014) concerns the activity with which the exploited data may be presented to the end use. Converting complex information into visually engaging charts and images is a very niche value proposition few firms specialize in. Usually, firms couple the visualization capability with other key activities such as analytics rather than offering it standalone. “Edinburgh CitySounds” is one such experiment selected for the second phase of OrganiCity. The experiment captures sounds by installing “auditory” data “sensor” devices (AASs) across the city. These AASs will capture short clips of ultrasonic and audible noises of bats, birds and other wildlife, traffic, and human activity in real time. These sounds in turn are aggregated with other data sets such as light, temperature, humidity, pollution to answer questions pertaining to the impact of human activity on animal behavior, changes in human/animal behavior with exogenous variables. It is imperative for Edinburgh CitySounds to develop visual standards to represent these seemingly unstructured, inconsistent, incoherent data sets, in doing so greatly enhance the utility of the final offering.

Target Customers

The basic premise of an OrganiCity experiment is to tackle an urban challenge. Consequently, the experimenters would look to deliver to any one or more stakeholders in an urban setting. Stakeholders such as citizens, other businesses, and city councils/governmental organizations could all be the key customers for experimenters. Moreover, unlike traditional businesses that mostly focus on one customer segment at a time, business models in an urban setting have a more complex interwoven nature with various stakeholders. Often seen are experimenters that deal with multiple customer segments at the same time. This is also seen as a way of achieving larger market needed for eventual viability of the business model.

Green roof monitoring, an Oslo-based experiment, is an example for operating in multiple target customer segments. It offers multisensorial monitoring of vegetation for citizens, businesses, and the municipality. Another experimenter, “Leapcraft,” a sensing platform to measure air quality has the city council as a target customer, whilst developing citizen dashboards to communicate insights from air pollution measurements.

Revenue Models

As discussed earlier, most of these experimenters are still in the process of discovering stable revenue streams. Some of these experiments in their current state only lend support to the experimenting firm's other business units without generating any revenues themselves. Moreover, revenue models, like other business model components, are prone to frequent changes. We have observed six different revenue models adopted or planned by experimenters to extract value from their offerings: asset sale, usage fee, leasing, licensing, subscription fee and advertising fee. For instance, "Wayfindr" provides its customers consultation for setting up audio navigation services and charges a (usage) fee. Whilst, "AirPublic" provides insights on the air quality to the city councils that subscribe to its services. FSTR licenses the use of its carpooling application to businesses which in turn make it available for their employees.

Further into each of these revenue models is the actual pricing mechanism for services and/or products. Osterwalder's (2004) three broad characterizations of pricing mechanisms—fixed, differential, and market based—have been used by experimenters. Predictably, most of the experimenters that deal in the B2B and B2G segments, owing to their relative lack of bargaining power whilst dealing with larger businesses, have been playing the role of price taker rather than price maker. It has also been observed that only a handful of experimenters with IP protected assets were able to take the lead and set prices.

Cost Structure

On the continuum of value driven to cost driven, we have observed that most of the OrganiCity experimenters are aligned closer to value driven extreme. It could be due to an emphasis on innovative and novel solutions rather than cost-effective solutions by the reviewers. Having said that, there are some experimenters who emphasized delivering solutions in a cost-effective way in their value proposition.

Empati and Leapcraft are examples of cost-driven experimenters. Each one of them deliver solutions seeking to capture a market by offering a lower cost solution. For example, Leapcraft seeks to lower the cost of measuring air pollution and increase spread by developing mobile-based air quality sensors that traverse the city on vehicles. Besides, OrganiCity is created as a platform to facilitate experimentation. Facilitating experimentation includes minimizing overheads needed to run these experiments. By providing technical expertise, a legal framework and access to data sets, the platform has provided a frictionless environment for innovation. However, since all the experimenters have common access to these facilities, we have not delved deep into these provisions/factors as they do not distinguish between experiments.

Application of the Framework

In this section, we illustrate the application of the framework by describing common types of UDBM observed, along with case examples from OrganiCity to illustrate each. We have chosen six experiments that represent a heterogeneous application of the framework in terms of differing activities, resources, cost structure, revenue stream and target customers. It should be noted that some cases examined operate under more than one business model, i.e., a portfolio of business models to support multiple value propositions, whilst others integrate together aspects of the business models presented. Thus, the examples given are not stringent nor are they necessarily static and can evolve over time. For example, they may offer sensing and analytics as a product and/or a service arrangement.

"Sensing as a Service" Model

The "sensing as a service" business model typically focuses on the deployment and maintenance of hardware-based sensor devices along with cloud storage and a software-based interface for delivering descriptive insights to customers under a leasing arrangement. In some cases, sensor deployment is offered as a product, with a maintenance service provided, whilst the value-adding cloud storage, analytics and visualization of data is offered as a service via an app or browser-based software interface. The service is typically B2G, and some value-adding predictive and/or prescriptive insights may also be added.

Example: Air Pollution Data

Many cities struggle with the cost of having granularity, accuracy and insight of environmental data in their cities. For example, cost raises challenges for achieving sufficient granularity of pollution monitoring to street level, whilst achieving valid measurement. One of the approaches to addressing these challenges is to implement mobile mounted sensing at street level to increase depth of coverage. The Danish-based company Leapcraft has developed a Sensing as a Service implementation for air pollution monitoring. They can include such aspects as techniques and calibration for sensor deployment and maintenance. As experimenters with OrganiCity, they prototyped and trialled lower cost mobile mounted air pollution sensor devices to increase the granularity of air pollution sensing in the city. Key activities focus on (1) Generating environmental sensor data and (2) Procuring environmental open data in order to calibrate and validate their sensor data. Leapcraft generates and exploits near real-time numerical geospatial objective environmental data. They hope to enrich insights from sensor data by procuring and exploiting further sources of open data. The offering emphasizes a cost-driven proposition, in terms of the

<table>
<tr><td colspan="2">Cost Structure:
Cost (Value) driven</td><td colspan="2">Target Customers:
B2G – B2B</td><td colspan="2">Revenue Models:
Lease - Subscription</td></tr>
<tr><td colspan="3">Key Activities:
- Generate sensor data
- Procure environmental open data
Descriptive & predictive insights from transformed data
- Visualisations of data insights</td><td colspan="3">Key Resources:
- Sensor based Hardware capture device
- App based Software Platform delivery
- (Near Real-time & historic geospatial, objective, numerical) environmental data.</td></tr>
<tr><td colspan="6">Value Proposition: Sensing as a Service</td></tr>
</table>

Fig. 3 Sensing as a service

lower cost of sensors and reduced number of deployments, though they also offer value-adding cloud storage and analysis and visualization. See figure 3 for an overview.

Their value proposition is to offer the customers both hardware sensor capture devices and app-based software (dashboard) to deliver customers analytics and visualization capabilities for descriptive and predictive insights of environmental data. Their customers are either Business to Business (B2B) or Business to Government (B2G), and they offer CKAN pre-integration of data to cities as part of the B2G offering. The solution includes cloud storage capability whereby historical environmental data generated and procured is offered to customers for analysis and insight.

"Prescriptive Insights as Product" Model

"Prescriptive insights as product" concerns business models where data is generated and/or procured to provide prescriptive insights for the customer based on the gathered data evidence. Thus, the core value generated is prescriptive insights such as recommendations or a suggested course of action that typically results in cost and/or time savings for the customer. The provider demonstrates competence in AI/machine learning for optimizing recommendations and may include sensing as a product/service as part of its offering. For example, wayfinding app solutions that procure open data to offer wayfinding advice to citizens traversing the city. Such wayfinding apps rely on acquiring and processing data, including aggregating and transforming open data in order to carry out prescriptive analysis to deliver optimal routing. Models observed typically fall into B2G or B2C.

Example: Waste Fill Data

In the context of smaller urban municipalities, the deployment of sensor technology-based bins can be commercially prohibitive, and lower cost solutions are needed. Working with OrganiCity, Iotee Lab (WasteHero) developed and tested a technique and technology for retrofitting existing bins with ultrasound-based low-powered IoT sensors that can connect across LoRa, Sigfox, or NB-IoT networks. The organization offers hardware sensor capture devices and a browser-based platform to deliver customers both descriptive, predictive, and prescriptive analytics and visualization capability for bin fill measurement. These include prescriptive bin collection route planning and predictive foresight in terms of cost savings. As experimenters with OrganiCity, they co-created with citizens to develop a browser-based citizen front end also. The solution is oriented towards the B2G market and aligns closer to a value-driven model, in terms of the benefits of the solution, though also can be seen as cost driven in terms of lower cost of deployment. In this regard, the sensors are offered as turnkey product solution, whereby training is offered for customer employees to install the sensors. They are exploring additional revenue models such as lease and Performance based Payment (PBA). Hardware sensors generate near real-time geospatial dynamic objective environmental data and static geospatial objective infrastructure data. To enhance their offering in the future, procuring open data can improve the predictive and prescriptive analytical insights of bin collection. In other words, festivities, events, and other contextual data could enhance their offering. Refer to figure 4 below for an overview.

"Analytics as a Service" Model

"Analytics as a service" business models focus on delivering software-based interfaces that deliver value-driven insights from procuring and effectively exploiting open and proprietary data. This model emphasizes value-adding activities of processing data (i.e., preparing, aggregating, transforming), as well as analytic and

Cost Structure: Cost-Value driven	**Target Customers:** B2G	**Revenue Models:** Sale
Key Activities: - Generate sensor data - Descriptive, predictive & prescriptive insights from transformed data - Visualisations of data insights	**Key Resources:** 1. - Sensor based Hardware capture device 2. - Browser based platform delivery 3. - (Near Real-time & historic	
Value Proposition: Prescriptive Insights as a Product		

Fig. 4 Prescriptive insights as a product

visualizing capabilities that give customers value-adding insights. This business model typically relies on procured data and is thus heavily dependent on sustainable partners and/or Service Level Agreements (SLA) from open data to remain viable. Offerings observed include B2G, B2B and B2C.

Example: Open Government Expenditure Data

Leveraging an increasing quest for open government and transparency, Spend Network delivered a browser-based interface to display and analyze public expenditure data. A value-driven cost structure and subscription-based Freemium revenue model has been established, whereby aggregated spending information is available for free through the website, and users are charged through subscription for additional features. These include: (1) the provision of procured and prepared open government data—to enable further independent analysis and (2) the provision of descriptive as well as predictive analysis/insights from aggregated government expenditure data including information about both supplier and buyer landscapes. An overview is given in figure 5 below.

Business and government sectors are the target customer segment. Spend Network procures objective historical open data to extrapolate trends. This consists of both static and dynamic open data, and textual and numerical open data. Geospatial data is not currently part of its offering.

Key activities undertaken as part of this value offering include Data Acquisition and specifically procurement of open government data, data exploitation and visualization. Whilst the solution is described as the provision of "raw data," in fact processes of data cleaning—i.e., prepare—and some aggregation are conducted on the data initially procured. Extensive manual data cleansing and cleaning processes ensure sufficient quality and accuracy. These are in place to address the challenge of obtaining relevant and accurate data in a situation where contracts or any other form of agreement to ensure provision of data are lacking.

<table>
<tr><td>Cost Structure:
Value driven</td><td colspan="2">Target Customers:
B2G – B2B</td><td>Revenue Models:
Subscription</td></tr>
<tr><td colspan="2">Key Activities:
- Procure open data
- Prepare, aggregate & transform data
- Descriptive & predictive insights from transformed data
- Visualisations of data insights</td><td colspan="2">Key Resources:
- Browser based Software delivery
- Processed open government data</td></tr>
<tr><td colspan="4">Value Proposition: Analytics as a Service</td></tr>
</table>

Fig. 5 Analytics as a service

"Recognition as a Service" Model

The "recognition as a service" offering centers around innovation in Artificial Intelligence (AI) capability to extract, identify, and in some cases understand the characteristics inherent in generated and/or procured data. These services may range from computer vision (e.g., identification and understanding of characteristics inherent in captured images or videos) to sound recognition (e.g., identification and understanding of characteristics inherent in audio recordings) and thus rely on superior resources and capabilities in data science techniques. Common examples include video sensors that count vehicles, people, etc. and audio sensors that recognize types of sounds. These organizations focus on analysis that is "predictive description," and revenue models observed are typically via sale, subscription, or advertising, and sensor deployment and maintenance may form an integral part of the offering.

Example: Noise Pollution Data

Increasingly, noise pollution is seen as a key factor impacting the quality of life in urban environments. It is therefore vital for the city authorities to manage and control noise to make cities more livable. One of the bottlenecks, from a technological standpoint, is to accurately measure the noise levels in real time across the city and to isolate the sources of noise to arrive at actionable insights. Sensifai, a Brussels-based OrganiCity experiment, set out to address these challenges. With support from OrganiCity, they prototyped solutions that capture high-quality, near real-time geospatial audio data by using auditory and geolocation sensors fitted to moving vehicles. Sensifai generates sensor-based data via a hardware capturing sensor device. This data is then transformed and analyzed using artificial intelligence enabled deep learning methods to extract subjective (types of noise) "predictive description" and objective (noise level and location) descriptive insights on noise. These insights are visualized onto a noise map which can be accessed by various stakeholders including citizens and delivered through a public browser-based interface. Thus, the service is value driven in terms of visualizing descriptive and predictive insights, both objective and subjective in nature. The offering is cost effective in terms of coverage and granularity by traversing the city with mobile mounted sensors. See figure 6 for an overview.

Although their initial target customer segments are citizens (B2C) and the government (B2G), they hope to eventually offer services to businesses (B2B), primarily real estate agencies, to identify tranquil spaces in the city of benefit to client advice, pricing and planning. In its current form, advertising on the website drive their revenues. They plan to be able to validate the offering to an extent where businesses approach them to purchase deeper insights into the city's noise landscape.

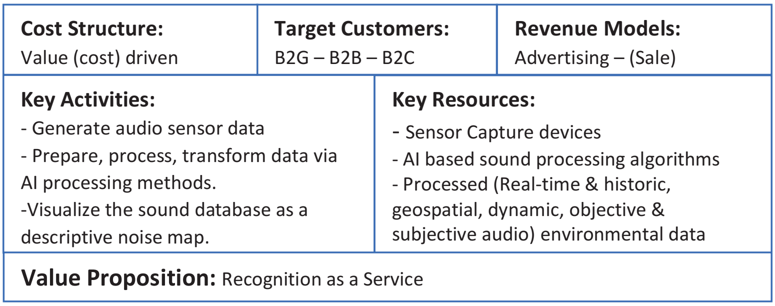

Fig. 6 Recognition as a service

"Automated Service Interaction" Model

The "automated service interaction" business model focuses on exploiting conversational AI and rule-based dialog technology, including natural language processing (NLP), and data ontologies to offer automated conversational agents in fulfilling information service provision. Key activities involve acquiring and processing citizen data in order to offer descriptive and prescriptive analytical insights of procured data to citizens. This may entail developing rule-based dialog flows and/or NLP to match citizen requests with procured data. Communication may be either textual or verbal via speech recognition. The customer is B2B or B2G, and many offerings typically rely on partners to deliver AI and rule-based dialog capability.

Example: Open Urban Data

An important consideration in the delivery and uptake of smart city services include the digital divide and convenience factors across various cohorts of citizens. This necessitates that governments facilitate easy and intuitive service delivery interfaces. TalkingCity, an OrganiCity experiment in the city of Aarhus, prototyped a platform for conversational style information service provision. These "Chatbots" use natural language processing techniques to communicate and understand citizen requests. TalkingCity acquires data through both procuring open data via API based software and generating user-input data via app/browser-based software. In terms of procuring open data, they connect to various open data platforms to extract data required to answer citizen queries. This consists of ingesting citizen queries, recognizing intent, connecting with open data platforms and generating a response back in natural language. TalkingCity procures all kinds of open data ranging from real time to historic, static to dynamic, objective to subjective, and environmental to governmental. Thus, a key activity is preparing, transforming, and exploiting data to deliver descriptive and prescriptive insights based on queries. Software capture of user-input data is via app-based or browser-based (third party) interface and delivered via the same medium. Thus, these "Chatbots" work over popular existing interaction channels such as Facebook, Whatsapp, Telegram, and Slack. An overview is shown in figure 7.

Cost Structure: Value driven	**Target Customers:** B2G – B2B	**Revenue Models:** Sale and Usage
Key Activities: - Procuring Open Data - Generating User Input Data - Exploiting data using NLP for Descriptive/Prescriptive insight	**Key Resources:** - Algorithms to Natural Language Process (NLP) - APIs to enable cross platform intergration - Dynamic subjective textual citizen data	
Value Proposition: Automated Service Interaction		

Fig. 7 Automated service interaction

TalkingCity hopes to build the technology and as it matures, engages with various service providers that are both governmental and commercial. By such engagements, they hope to have access to revenue streams such as one-time setup fees, recurrent fees from platform hosting services and other support and training activities. The target customers include municipalities, city councils (B2G) and private businesses (B2C).

"Crowdsourcing Community Platform" Model

"Crowdsourcing community platform" models rely on citizen user input and/or citizen's smartphone sensors to acquire various types of urban data. The focus is typically on galvanizing citizens to generate urban data around specific issues, topics or challenges. The offering is via app and/or browser-based software and relies on network effects or a critical mass of users to add value and sustain. In some cases, citizen derived data is procured via tracking from social media sites in order to visualize aggregated data (e.g., hash tagging tranquil places in the city) on an app or browser-based interface. The revenue model is typically via B2G sale or B2C advertising and/or public funding.

Example: Infrastructure Data

Digital technologies have begun to be leveraged for preserving the cultural heritage of cities and promoting urban renewal efforts. This in concert with community-driven efforts can promote democratization in producing the city, whilst reducing cost of data gathering through crowdsourcing initiatives. The social enterprise and OrganiCity experimenter, "Space Engagers" has a mission to promote community renewal through combing citizens' crowdsourcing, mobile platform technology, and open data. Space Engagers, through its engagement in OrganiCity, developed its community engagement tool, to enable and support communities to generate urban data around issues such as vacant places and spaces. The experience in OrganiCity also enabled Space Engagers to scale the application across multiple urban environments. Space Engagers leverages a software app-based interface to capture and deliver data. Geospatial Visual Infrastructure data (images) and textual subjective and objective data (text comments) are generated through user input, whilst mapping data is procured as open data. Thus, the main source of data is obtained through crowdsourcing. As a result of the key activities of generating and aggregating data, the app features an interactive map (open geospatial visual data) to visualize pictures and comments on a specific area of the city. This in turn enables other participants to discuss potential community projects and to interact on possible ideas for addressing the challenges posted in the original upload. Examples of successful projects so far include several community-led urban regeneration initiatives as well as mechanisms through which governments can take more informed and citizens-centric decisions.

The cost structure can be viewed as value driven in terms of new modes of gathering urban data through tailored crowdsourcing-based apps. The target customer is B2G in terms of this social enterprise empowering citizens directly in engaging with urban issues. The development of the app has been ensured through revenue from public funding initiatives and does not rely on a typical revenue model of advertising, sale, or subscription. See figure 8 for an overview.

Conclusion and Future Work

This study has presented a framework of urban data business models, defined as a business model where urban data is the central to the value proposition. We analyzed 40 urban data focused experimental cases under the umbrella of the EU H2020 OrganiCity to inductively derive the framework. The framework composes five higher level dimensions based on the six dimensions we identified from the literature review. Through the exercise of developing the framework, we determined that "Value Proposition" will logically flow from other higher level dimensions of the

<table>
<tr><td colspan="2">Cost Structure:
Value driven</td><td colspan="2">Target Customers:
B2G</td><td colspan="2">Revenue Models:
Public funded</td></tr>
<tr><td colspan="3">Key Activities:
- Generate user input based data
- Procure open data
- Aggregate and visualise data</td><td colspan="3">Key Resources:
- Geospatial infrastructure data
- Qualitative textual data
- Software app based interface</td></tr>
<tr><td colspan="6">Value Proposition: Crowdsourcing community platform</td></tr>
</table>

Fig. 8 Crowdsourcing community platform

framework and thus was not included in the final framework. In other words, “data” or resulting “knowledge” or “insight” is reflected through the activities a business undertakes to exploit and visualize the data, and thus captured through the framework. This also avoids the problem of multicollinearity which would affect subsequent clustering of business model types when applying the framework.

Through the analysis of cases, we determined that “Key Resources” should compose of both urban data capturing and delivering hardware and software, as these were a core offering of many of the cases we explored. Comparing the existing literature, this is implicitly referred to by Rizk et al. (2018) as product or application-based “Service Interaction,” as “Technological effort” by Engelbrecht et al. (2016) and by Hartmann et al. (2016) through sub-dimensions of “Data Sources” and “Data Generation.”

As a result of the literature review, the variables in our framework have carefully been identified to avoid inter variable redundancies, thereby making the framework amenable for developing a taxonomy of urban data business models. For example, we argue that sourcing the data is a key activity, and not a key resource, whereby Hartmann et al. (2016) already captures “Data Generation” and “Data Acquisition” as an activity in addition to capturing these through the “key sources” that he distinguishes.

In order to illustrate the applicability of the framework, we have selected six heterogeneous cases from OrganiCity to illustrate differing urban data business models. The next stage of the study will be to apply the framework to all OrganiCity supported cases to cluster and classify business models types. We furthermore plan to apply the framework to existing businesses which have already established a sustainable business model to identify trends within the industry.

As touched on in the introduction, we believe the framework can be useful for researchers as a common language and analytical lens in (1) understanding challenges across the value network in developing urban data business models, (2) identifying opportunities for value propositions and related urban data business model combinations, and (3) substantiating the types of urban data business models. Furthermore, the framework may be drawn on by practitioners in assessing proposals for funding and support, including viability in the context of the funding and the challenges with which to develop a solution.

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