A Systematic Review for Smart City Data Analytics

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Smart cities (SC) are becoming highly sophisticated ecosystems at which innovative solutions and smart services are being deployed. These ecosystems consider SC as data production and sharing engines, setting new challenges for building effective SC architectures and novel services. The aim of this paper is to “connect the pieces” among Data Science and SC domains, with a systematic literature review which identifies the core topics, services, and methods applied in SC data monitoring. The survey focuses on data harvesting and data mining processes over repeated SC data cycles. A survey protocol is followed to reach both quantitative and semantically important entities. The review results generate useful taxonomies for data scientists in the SC context, which offers clear guidelines for corresponding future works. In specific, a taxonomy is proposed for each of the main SC data entities, namely the “D Taxonomy” for the data production, the “M Taxonomy” for data analytics methods, and the “S Taxonomy” for smart services. Each of these taxonomies clearly places entities in a classification which is beneficial for multiple stakeholders and for multiple domains in urban smartness targeting. Such indicative scenarios are outlined and conclusions are quite promising for systemizing.

CCS Concepts: • **Applied computing → Enterprise computing**; *Enterprise ontologies, taxonomies, vocabularies* • **Information systems → Information system applications**; *Data mining* • **Information systems → World Wide Web → Web applications**; *Crowdsourcing* • **Human Centered Interaction → Ubiquitous and mobile computing**; *ubiquitous and mobile devices*

KEYWORDS:

Data mining, data harvesting, smart cities, smart dimensions, smart services, systematic review, taxonomy, Internet of Things, crowd–sourcing, crowd–sensing, open data

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1. INTRODUCTION

Smart cities (SC) have changed radically, since the initial appearance of the term in literature in late 1990s due to the impact of disruptive technologies and new forms of interaction in the everyday life. Multiple stakeholders act in parallel with joint forces of governments, industries and scientists who transform cities of today. Urban challenges have been addressed from different perspectives by the primary SC actors so far: *governments, policy makers and municipalities* (e.g., EU smart cities initiative[1], World Smart City Forum[2], Smart City Business Institute[3]) have structured progressive policies to deal with issues like urbanism and climate change, with one of the most recent to be the United Nations 2030

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https://doi.org/10.1145/3239566
[1] http://ec.europa.eu/eip/smartcities/
[2] http://www.worldsmartcity.org/
[3] http://www.smartcbi.org/

Agenda for sustainable development[4].On the other hand, *industries with the leading role of the information and communication technologies* (ICT) (e.g., CISCO[5], IBM[6], Libelium[7], Ericsson[8], etc.) define a new competitive market that is estimated to become dominant by 2030 [1]. While, *scientists* investigate the future of an interdisciplinary and much promising domain that combines studies like engineering, ICT, humanities, ethics, political science, etc.

In this respect, several scholars [1–7] as well as standardization bodies (e.g., the International Telecommunications Union (ITU)[9], the International Standards Organization [8], etc.) provide with alternative definitions, conceptual models and architectures for SC, in their attempt to clarify different contextual and organizational issues. An indicative SC definition comes from ISO/IEC [9] and recognizes the smart and sustainable city as "*an innovative city that uses ICT and other means to improve quality of life, efficiency of urban operation and services, and competitiveness, while ensuring that it meets the needs of present and future generations with respect to economic, social and environmental aspects*". Moreover, a widely adopted smart city conceptual framework analyzes the SC in six dimensions, in an attempt to define indexes that can measure urban intelligence (Fig. 1) [10]: *i) smart economy, ii) smart mobility, iii) smart environment, iv) smart people, v) smart living and vi) smart governance*.

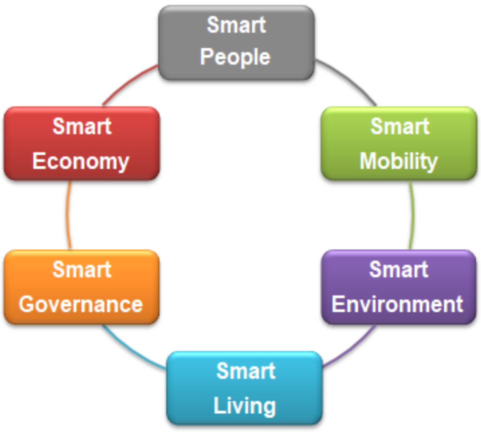


Fig.1. The six dimensions of smart cities

Since SC involve multi–layered entities (devices, installations, applications), SC architectures are needed to define the different hard and soft facilities, which provide several –so called– smart services to and from local stakeholders [11]. These services range from upgraded typical city utility services (i.e., water, energy, gas, etc.) to enhanced content (i.e., optimal transportation mean's selection for mobility in the city) or other types of ICT–based services (i.e., government, health, education and tourism, etc.). SC produce large scales of data constantly and in evolving rates. Data is produced from sensors and devices, from applications and services, and from social media and digital platforms. Effectively handling data is crucial for improving SC life and for safeguarding its dynamics and momentum.

At most recent studies ([1], [12–17]), urban data or city data (or SC data), i.e. data produced in the city's operation context [18], is recognized as a significant asset for the deployment of SC. It is now evident that a novel sector the so–called "data economy" emerges. In SC data economy, new business models, which utilize and correlate data to reveal their analytics, will drive the cities future. In specific, urban data collected from the Internet–of–Things (IoT) infrastructures and analyzed with different methods can largely improve several monitoring and response tasks and services (i.e., [19–23]). SC data impact multiple services in various inter–disciplinary domains such as in smart transportation, resource efficiency, crowd–source based services, etc. [23–25]. For example, Transport Management Systems (TMS) operation is based on the use of real–time data (e.g., social media data for the detection of traffic congestions, road accidents, etc.) and on new technologies (e.g., smart cars, smartphones, etc.), aiming to save time and citizens' road safety [23]. The importance of crowd–sensing and Big Data that summarizes data sources, analytical approaches and application systems through the introduction of social transport for the deployment and improvement of Intelligent Transportation System (ITS) services is also highlighted by [24] and [25]. Cisco[10], also, claims that cities leveraging their data may attain increasing their energy efficiency by 30%.

A recent survey [280] has revealed that there are 4.9 billion connected objects, which are expected to reach or exceed 50 billion in 2020 and over than 1.4 billion smartphones; while the market of RFID tags is worth $11.1 billion and 500 million vehicles expected to be connected to the Internet by 2020. Specifically, according to Statista[11], 1.8 billion connected objects were within smart cities in 2015, while this number is expected to reach 3.33 billion in 2018. The existence of these interconnected objects results in the real–time production of an astonishingly large number of urban

[4] https://sustainabledevelopment.un.org/post2015/transformingourworld
[5] http://www.cisco.com/c/en/us/solutions/industries/smart–connected–communities.html
[6] http://www.ibm.com/smarterplanet/us/en/smarter_cities/overview/
[7] http://www.libelium.com/libeliumworld/smart_cities/
[8] https://www1.ericsson.com/news?tagsFilter=smart+cities
[9] http://www.itu.int/en/ITU–T/focusgroups/ssc/Pages/default.aspx
[10] https://www.postscapes.com/anatomy-of-a-smart-city/
[11] https://www.statista.com/statistics/422886/smart-cities-connected-things-installed-base/

data offering unlimited opportunities for gaining profound insights of the cities of today and knowledge out of them is not yet fully exploited, as this data is often scattered or unavailable [281]. However, many local authorities (Amsterdam, Dublin, Singapore, City of Chicago, Los Angeles, NYC, etc.), recognizing the impact of urban data in their cities and seeking to turn into smart cities, are striving to manage and exploit their data. The need to investigate how urban data is produced, circulated, monitored and exploited in SC has been the motivation for conducting the current study.

It is already well recognized that SC data and their volumes impact and shape the cities of today and tomorrow [282]. The demand to understand how data are produced, circulated, monitored and exploited, will become more intense in the next period since data are constantly produced from multiple devices and IoT installations with such high rates that gaining insight and knowledge out of them is not yet fully exploited. The aim of this survey is to contribute in understanding the urban data types, their production sources, and their exploitation practices by a systematic review which addressed the different involved features and entities. Such a systematic review is very important due to the above significant role and impact of data in SC. According to the authors' knowledge, although an abundance of publications refers to data and SC, a systematic analysis which connects the "pieces" between Data Science and SC is still missing. The current article is a comprehensive survey which examines the way in which urban data are used in SC, covering the period 1996–2017. Specifically, this article focuses on how data is produced, collected, stored, mined and visualized in SC in order to focus on the knowledge and the hidden information revealing as tools for creativity and innovation. Initially, the basic principles associated with urban data are discussed, and then the research methodology is presented. Urban data sources and urban data types are identified, data collection and data mining processes at SC are deeply studied and the smart services, which have been developed so far, are emerged. Based on this extensive review, a novel set of taxonomies is built by exploiting the review's qualitative outcomes. The proposed taxonomies cover the SC data entities and methods which contribute in delivering valuable tools for researchers and developers working in data–driven SC approaches. More specifically the overall so called "DMS" taxonomy set includes: the "D Taxonomy" to classify the data production entities, the "M Taxonomy" to categorize and highlight the data analytics methods, and the "S Taxonomy" which identifies the context of the most crucial smart services. The "DMS" taxonomy is scalable and extensible since it has systematically summarized the state of the art articles but it can also be extended to include new and forthcoming advances in the area.

The remaining of this paper is organized as follows: Section 2 discusses the theoretical background and highlights this article's objectives with emphasis on Data Science's fundamentals under the SC lens. Section 3 contains the systematic literature review methodology that was followed and which has set this article's research questions, while Section 4 discusses the quantitative and some of qualitative outcomes. Section 5 introduces the novel "DMS" taxonomy, while the current trends are presented in Section 6. Finally, Section 7 contains the conclusions of the article and future potentials.

2. BACKGROUND

SC ambiguous definition and conceptualization has triggered standardization processes which are under development, in an attempt to clarify the domain and homogenize the corresponding offered solutions [1]. Today, all standardization working groups [9], [11], [27–26] define models to communicate the SC concept to corresponding stakeholders (governments, communities, technology firms, service providers, developers, etc.), which all recognize data to be a significant element for SC realization. ISO 37120 for instance, introduces several indexes to measure urban performance and this measurement is based on data collection from several alternative resources. ITU recognizes data to be one of the major SC "soft facilities", which feeds each of the offered set of smart services. Furthermore, British Standard Institution (BSI) [27] views SC as a system that consists of several subsystems (so–called "infrastructure–based" and "service–based" sectors) (Fig. 2a), where data is produced and collected via sensors from different hard facilities (energy, transport, water and waste) or in service–based sectors (health, education, safety and social media); it is stored in city data storages; flow over SC infrastructure (telecommunications and electronics); analyzed; and displayed on city dashboards or delivered to services' end–users. The BSI's approach is followed in this article (Fig. 2b) and explained in the following subsections, where city appears as "data engine" and data flows follow a circular process, since –even during the last step– the analyzed data is stored and compared with other collected information or it returns back to the community as the context of new smart services.

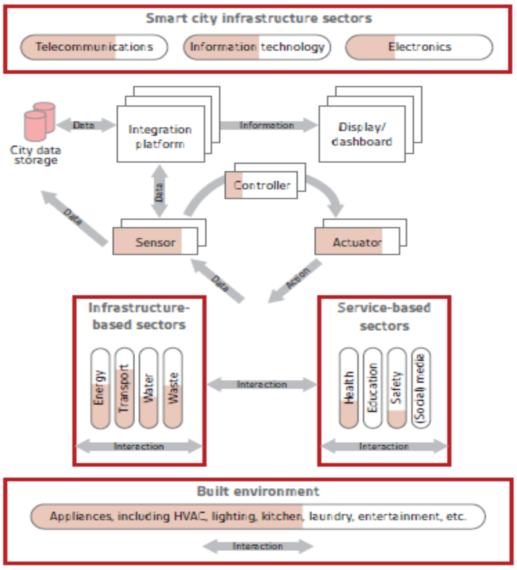


Fig. 2a. City as a “data system” [27]

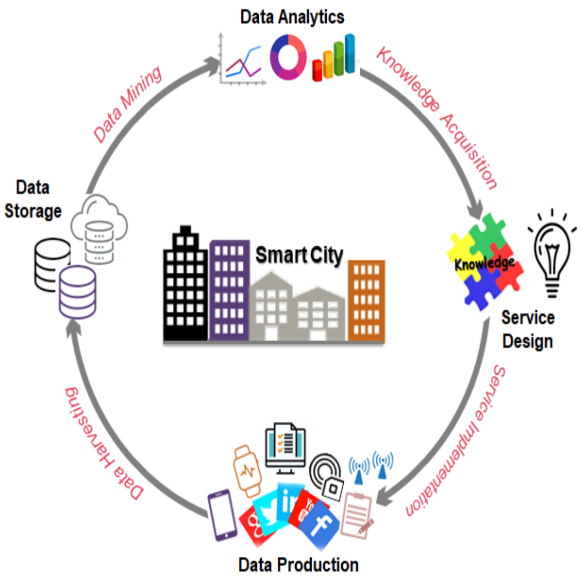


Fig. 2b. Smart city as a “data engine”

Since our study focuses on the production, processing and analysis of SC data, next subsections offer a summary of the basic principles related to the urban data sources and the analytics approaches. Subsection 2.1 refers to the production of urban data and its features, while subsection 2.2 involves the data analytics basics, focusing mainly on “Data Harvesting” and “Data Mining” processes.

2.1 Urban Data Sources

Cities have become actual “data engines” which constantly produce and consume data. A huge variety of devices (sensors and mobile equipment) and applications act as data sources, which record multiple everyday activities, from everywhere and produce large scale of heterogeneous datasets. Urban data is produced either, directly during daily activities and smart service execution (e.g. social networks, smart applications, etc.) or it is collected via sensing devices, which can be either fixed or portable (e.g. environmental sensors, traffic sensors, motion detectors, mobile devices, wearable devices, etc.). The differentiation of SC data sources typically involves two major data origins levels [1]:

— *Internet of Things (IoT)* data production from sensors and actuators embedded in physical objects which are linked through wired and wireless networks [28]. This “umbrella” term involves all the interconnected smart devices, such as Radio Frequency Identification (RFID) tags, sensors, cameras, mobile devices, Near Field Communication (NFC), etc.

— *Crowd–sensing* data production coming from the engagement of a defined “crowd” of individuals for obtaining required services, contents or ideas, also known as Crowd–sourcing [29]. The extension of crowd–sourcing when it is related with sensors or sensing capability is named Crowd–sensing. Crowd–sensing when using mobile devices, (wearable devices, mobile phone applications, etc.) is more specifically referred as Mobile Crowd–Sensing and Computing (MCSC) [30]. Crowd–sensing, has largely contributed in the definition of the so–called Internet of People (IoP) [31], which is extending IoT with human experience and capabilities. Several times IoP is used independently or in combination with IoT, while it often helps to verify the data coming from IoT sources [32].

Data derived from the urban data sources, is characterized by heterogeneity and it typically is of big data scale, based on the Gartner [33] big data definition: “*Big Data is high–volume, high–velocity and/or high–variety information assets that demand cost–effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation”*. SC data fall into the Marr [34] big data definition which identifies the five big data characteristics, known as *5V's* which are: *i) volume, ii) variety, iii) velocity, iv) veracity, and v) value*. This is due to the SC typical sources as for example, in the case of environmental sensors which produce numerical and periodic data, Facebook produces multimedia and real–time data, while censuses offer alphanumeric and offline data of large scale and evolving rhythm.

With regard to data ownership status, urban data may be closed, shared or open [35]. Closed data contains personal and sensitive information and can be strictly accessed by its owner (e.g. financial data that comes from companies, health data, etc.). Shared data is published with the name of its owner (e.g. published surveys, social media data, etc.). In case data is accessible and available for everyone to acquire, use and process without restriction for copyright, it is called *Open Data* [36]. The development and management of open datasets is very crucial for SC since they enhance decision–making, citizen engagement and data economy. Many local government agencies and public organizations have deployed open data platforms such as NYC Open Data[12], DataSF[13], London Datastore[14], Transport for London[15], to effectively contribute to the deployment and implementation of SC, while European Commission[16] has funded a lot of projects on open data for SC (i.e., European Data Portal[17], EU Smart Cities Information System[18], Open Cities[19], Organicity[20]).

2.2 Data Analytics Basics

Data production in SC sets new challenges when it comes to revealing patterns, detect norms and phenomena in the city context. SC data analytics is an important approach towards improving city experiences, quality of life and city services. Such analytics require *"Data Mining"* and *"Data Harvesting"* solutions which are often inter–changed and correlated. As depicted in Fig.2b, the role of these two different approaches is important at different levels. Data harvesting drives processes from data production to their storage and management level, while data mining receives the stored data to produce intelligence and analytics.

In the Data Science context, *"Data Harvesting is the gathering of data from numerous disparate databases into a single database from which it can be re–published in a unified manner"* [38]. The data harvesting process involves the acquisition and recording of data and it is accompanied by data pre–processing and storage in an attempt to generate useful and qualitative data sets. Urban *raw data* is characterized by heterogeneity (different types, duration, format), while may contain noise and be inaccurate [39]. *Data Pre–processing* process affects the quality of collected data and consists of the following methods: *i) Data Cleaning, ii) Data Integration, iii) Data Transformation and iv) Data Discretization* [40]. Then, depending on the portability and usability requirements, the pre–processed data sets are stored either in *traditional databases (DBMS)* or in *cloud storages*, while according to its type is stored either in *Graph DBMS*, or in *DBMS/SQL*, or in *NoSQL* (key–value stores, document stores, column–family stores, graph databases), or in other data storages [41–43]. Respectively with other data categories (business data, healthy data, financial data, statistics, etc.), the pre–processing process of massive and complex urban data collected from various sources and the flexible storage means (i.e., NoSQL, scalable cloud data storages, etc.) are crucial for the acquirement and management of high–quality data sets that will facilitate the data analysis and offer worthwhile and accurate insights [37], [279].

According to Kantardzic [44], "*Data Mining is a process of discovering various models, summaries and derived values from a given collection of data*". Data mining process is used for i) searching non–trivial information and patterns and ii) predicting unknown values from available huge volumes of data, utilizing, respectively, descriptive and predictive methods. Such popular methods involve: *(i) Clustering; (ii) Classification; (iii) Regression; (iv) Summarization; (v) Dependency Modeling; and (vi) Change and Deviation Detection.* Overall, data mining is an interdisciplinary process that incorporates and utilizes many techniques and methods from other fields such as *data warehouses systems*, *statistics*, *machine learning*, *visualization*, *fuzzy logic*, *artificial neural networks* and other [44]. Data mining in SC context, is used to investigate and extract urban patterns related to the daily city operation and citizens (e.g., transport system conditions, environment quality, community activities, consumer patterns, etc.), as well as, to predict and prevent of future situations (e.g., resource management, delinquent behavior prevention, etc.) [37].

"Urban Data Analytics" as a term is used to encapsulate techniques that are used to analyze and acquire profound knowledge out of urban data. Since urban data are produced from the sources highlighted in subsection 2.1, multiple data type are produced such as: i) text, ii) audio, iii) video, iv) social media, and v) metadata. Depending on each SC data analytics case, these data types are the sources for data harvesting over which then various methods such as data mining, machine learning, statistical/predictive/graph analysis, etc. are implemented to gain knowledge and to advance SC intelligence detection [45]. The gained insights by data analytics, can synthesize the city profile bringing out the urban potentials but also city's weaknesses and problematics. Taking into account the acquired knowledge, decision–makers (local governments, businesses, researchers), according to their interests, suggest, design and implement new services

[12] https://opendata.cityofnewyork.us/
[13] https://datasf.org/opendata/
[14] https://data.london.gov.uk/
[15] https://opendata.cityofnewyork.us/
[16] https://ec.europa.eu/digital–single–market/en/open–data
[17] https://www.europeandataportal.eu/en/highlights/open-data-european-cities
[18] http://smartcities-infosystem.eu/
[19] http://www.opencities.net/content/project
[20] http://organicity.eu/

that can increase city's "intelligence". These new services, in turn, feed back new data production cycles following an iterative approach at which urban analytics can drive innovation in a continuous agile refinement manner.

3. RESEARCH METHODOLOGY

Our research interests, the identification of research gaps discussed in Section 1 and the intense debate in the academia and business circles around the SC, have led us to conduct the present systematic review. The study has followed a methodology to determine how scientists have approached SC data production, harvesting, and analytics and to offer insights and understanding of the corresponding state–of–the–art. In this context, the proposed methodology has identified "schools of thought" which had major contribution in this domain.

Systematic literature reviews are secondary–level studies and the quality of their findings is significantly dependent on the quality of the primary studies they use. An initial search for relevant studies on the Internet for the period 1996–2017, returned 2,312 articles. Due to the large number of references in the area, it was considered necessary to adopt a systematic methodology that would help to limit the initial number of articles based on strict criteria. The adopted methodology is based on the guidelines that were introduced by Kitchenham [46–47]. The selection criteria of this method concern the review process's novelty, systematic approach and comparative advantages, such as the completeness and rigor. These software engineering – oriented guidelines offer the basic and essential principles required for a complete and systematic – literature review, contributing to the selection of qualitative empirical studies and time–saving [48]. This method is chosen since it follows a uniform protocol, which unfolds in *three phases* with the next specific stages (outlined in Fig. 3):

i. the *Planning Phase*, to identify the review's contribution and describe the review protocol;
ii. the *Conducting Phase*, to follow the step–by–step review protocol;
iii. the *Reporting Phase*, to deliver an overall presentation and the peer review of the systematic review.

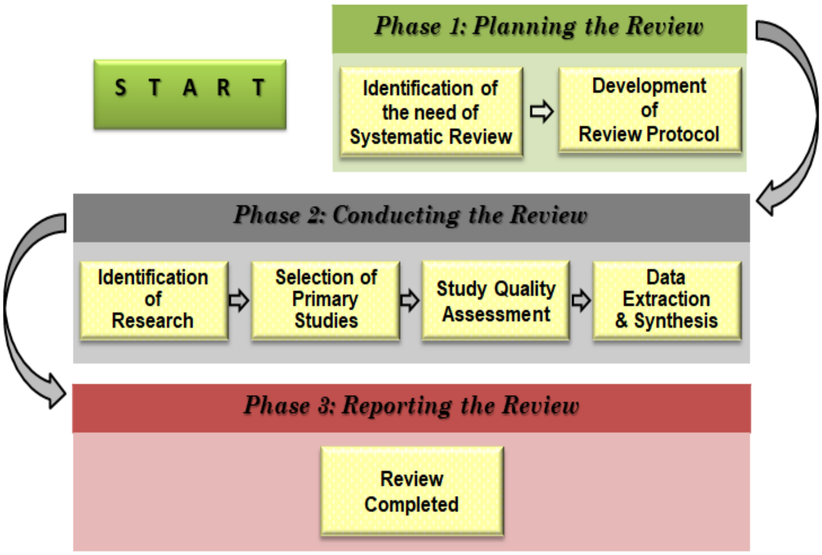


Fig.3. The phases of systematic review process

Each of the systematic review phases is detailed in the next subsections.

3.1 Phase 1: Planning the Review

Phase 1 involves two stages, the first of which clarifies the need and the novelty of the systematic review, and the second concerns the drawing up of the review protocol.

Stage 1.1: Identification of the Need for a Systematic Review
The first stage of the Planning Phase is the identification of the need for a Systematic Review. The study of SC in the Data Science context is an interesting topic and there is an abundant amount of related articles, which is growing exponentially as it is documented in Section 4. Several literature studies were referenced in the Introduction with regard to IoT, big data, data analytics and SC (methodologies, architectures, models, etc.). Nevertheless, none of them focused

on this article's objective with regard to connecting the pieces between data science and SC or explicitly investigating data harvesting and data mining under the SC lens, while no similar work could be located.

Stage 1.2: Development of the Review Protocol
It is the most crucial stage of the process since it analyzes and describes the actions that have to take place before the Conducting Phase. The review protocol is refined during the entire process of the systematic review. Thus, in this stage the emerging research questions, the search strategy and the selection criteria are discussed and identified.

3.2 Phase 2: Conducting the Review

In the Conducting Phase the actions that are delineated in the Protocol Development Stage (Phase 1) are carried out. The stages of this phase follow a sequential flow which can iterate since many activities which initiate at the protocol development stage, need to be refined as the review is implemented.

Stage 2.1: Identification of Research
This is a pivotal stage in every systematic review since the research questions which drive the review's goals are defined under the consideration of three major views:

i. the *Population* that corresponds to the individuals or records of the investigation topic (e.g., studies related to data analysis on smart cities)
ii. the *Interventions* that addresses the alternative approaches and methods to the topic and/or their comparison (e.g., data analytics methods, smart services, etc.)
iii. the *Outcomes* that reflect results and factors, which can be used for the interventions' comparison (e.g., algorithms, smart applications, etc.).

As described in Section 2, the several issues with respect to the cycle(s) of data production, data harvesting and data mining in the SC context, raise many challenges which are addressed in this review by setting the most important next research questions :

RQ1. How many research studies exist that address the data harvesting and the data mining processes in SC?
RQ2. Which methods were used for the harvesting and mining of urban data?
RQ3. Which smart services utilize urban data in smart cities?
RQ4. What are the most common sources and types of storage of urban data?
RQ5. Which smart applications utilize or produce urban data?

These questions are adapted to the followed review protocol since research question RQ1 is associated with the Population perspective, questions RQ2 and RQ3 are related to the Interventions perspective and questions RQ4 and RQ5 cover the Outcomes perspective.

Stage 2.2: Selection of Primary Studies
The common methods for searching articles are the following: i) the manual search in specific journals and conference proceedings, ii) the broad automated search in digital libraries, iii) the snowball technique (backward or forward), and iv) a combination of the upper methods [49]. Our search strategy was based on the broad automated search in digital sources and was carried out in the time period June – August 2017 focusing on the articles that have been published in journals and conferences. This method, in spite of its disadvantages (time–consuming procedure, irrelevant articles), is exhaustive and impartial as includes all the possible results regardless of the mean of publication. The selection of the most appropriate digital sources (digital libraries and indexing systems) and the determination of the search terms are necessary for the implementation of the broad automated search method.

The sources that were used in the present review were the following indexing systems and digital libraries due to their wide and universal adoption in the academic communities and their free access given to academia [50–51]: *Google Scholar*[21]*; Scopus*[22]*; IEEE Xplore* [23]*; and Science Direct*[24].According to Brophy & Bawden [53], Google Scholar offers coverage and accessibility and the digital libraries (IEEE Explore, Science Direct, etc.) are preferred for the results' quality, while both of them are accurate. Taking into consideration these findings and in order to get the best possible search and collection of the existing research articles related to our study, the two search systems were combined.

The search in the aforementioned digital sources was carried out using appropriate search strings combined with Boolean operators following the guidelines of Spanos & Angelis [49], who have explained, in their work, that "the determination of search terms is an iterative procedure starting with trial searches using different search terms,

[21] https://scholar.google.gr/
[22] https://www.scopus.com/home.uri
[23] http://ieeexplore.ieee.org/Xplore/home.jsp
[24] http://www.sciencedirect.com/

considering an initial set of articles that is already known to belong to the research field of the systematic review. The procedure of determining search terms ends when the initial set of already known articles is found by the search". In our case, the search terms were used **«"***Data Harvesting" AND "Smart Cities"»* and *«"Data Mining" AND "Smart Cities***"»**. The search has been conducted for the period 1996–2017, as the notion "smart city" has first appeared in 1996 according to [53], [1], and was based on the title, the keywords and the citations of the articles to get the most relevant articles as search results.

This stage is completed by the setting of the appropriate and well–defined ***inclusion/exclusion selection criteria*** according to them the candidate articles *are* evaluated and the final sample of the included articles is determined. In our case, the selection criteria are the following:

— ***Inclusion Criteria***

1. Articles published in Journal / Conference in which correspond at least three articles from those have found during the selection. This criterion applies only to the search string «"Data Mining" AND "Smart Cities"»
2. Articles that perform at least one study that analyzes the data harvesting processes/data mining processes on smart cities

— ***Exclusion Criteria***

1. Articles performing studies related to smart services and not to smart cities
2. Articles performing studies referred only to data harvesting/data mining processes or only to smart cities

Stage 2.3: Study Quality Assessment

According to Kitchenham [46] the Quality Assessment of articles is very difficult and depends on various factors. The adoption of additional criteria is needed to make certain that the high quality level of the included articles in a systematic literature review. The quality assessment criteria, which should be covered at least in part, for an article to be included in the present study were related to:

i. *the description of the data,* i.e. description and documentation of the terms, methodologies, surveys or results that presented or cited in the article (e.g. datasets, data mining algorithms, smart applications, other studies used in this article, etc.
ii. *the availability of the data,* i.e. information on access to aforementioned used data (e.g. URLs, DOI, databases, organizations that provide data, etc.)
iii. *the description of the used methodology,* i.e. detailed description and documentation of the methodology steps by citing fundamental axioms, rules, etc.
iv. *the presentation of the results,* i.e. comprehensive and coherent presentation using graphs, tables, etc.

Stage 2.4: Data Extraction & Synthesis

During this last stage, valuable information is extracted from the final sample of articles, which remained after "screening" and can provide with answers the above Research Questions. This knowledge is built on the exploitation and synthesis of the useful data features – selected manually by each inserted article. For their convenient processing and synthesis this data is encoded by the using some data features. The data features extracted from each article, based on our Research Questions are listed below:

i. *Authors, publication source and year of publication (RQ1)*
ii. *Type of article (Journal/Conference) (RQ1)*
iii. *Data harvesting and analysis methods (RQ2)*
iv. *Smart city dimensions and smart city services (RQ3)*
v. *Urban data sources and urban data types (RQ4)*
vi. *Smart applications (RQ5)*

The sequential execution of the stages of the Review Protocol extracted a final set of articles of our review. The results for the search terms «"Data Harvesting AND "Smart Cities"» and «"Data Mining" AND "Smart Cities"» are depicted in Fig. 4.

With regard to *"Data Harvesting" AND "smart city"*, 50 candidate articles were found, by performing the initial search process (Fig. 4(a)). The "screening" process left out 5 irrelevant articles. After studying the remaining articles, 13 more were removed as irrelevant based on the inclusion/exclusion and the quality assessment criteria. Consequently, 32 articles synthesized our final sample.

Similarly, *"Data Mining" AND "Smart Cities"*, led to selection of returned 767 candidate articles (Fig. 4(b)). This set was classified according to the publication type in *Journal Articles* (341) and *Conference Articles* (426). The *Inclusion Criterion 1* resulted to a subset of 117 journal and 142 conference articles that remained for further analysis. Their careful analysis excluded 40 journal and 47 conference articles as irrelevant according to the inclusion/exclusion and quality assessment criteria. In the end, *77* journal and 95 conference articles structured the final sample.

Fig. 4. Selection process of the articles final sample

The data features derived from the remained set of articles and their synthesis are presented, in detail, in the next sections (Sections 4 & 5).

3.3 Phase 3: Reporting the Review

The Reporting Phase concerns the final presentation and the assessment of the systematic review's results. The clarification of the systematic review's contribution depends on the effective presentation of its results to readers. Hence, the completed review should be documented, properly structured and well–written with coherent text flow.

4. SYSTEMATIC REVIEW RESULTS

This section outlines the survey findings and it is organized in two subsections. Subsection 4.1 summarizes the initial sample of articles and answers to RQ1, which concerns the number of articles address to data harvesting and data mining processes, while subsection 4.2 offers a general overview of the outcomes of the investigated articles.

4.1 Quantitative Analysis

Results to response to RQ1 are depicted in Fig. 5, which summarizes the corresponding amounts of works that address data harvesting (DH) and data mining (DM) with regard to SC. Studies with regard to DH in SC start appearing in 2010 and increase slowly until 2016 (21 articles), with a scholars' focus on data analytics omitting the previous stages of collection, processing and storage. Results scale up with regards to DM and SC: only a few studies (between 1 and 6) were published on an annual basis during 2000 and 2010. Nevertheless, they emerged radically and reached the amount of 315 articles in 2016, which was double the number of 2015's publications. Such results demonstrate an increasing corresponding interest of scholars, which utilize DM in SC in an attempt to collect and analyze urban information with several methods and algorithms. Most of the articles were collected from Google Scholar® (92.5%), while Scopus® (4.95%), Science Direct® (1.95%) and IEEE Explorer® (0.65%) to follow (Fig. 6). With regard to corresponding publishers (Fig. 7a), Springer journals have published the majority of articles (27%) followed by Elsevier (22%) and IEEE (19%). On the other hand (Fig. 7(b)), IEEE "leads the race" of conference organizers (65%), followed by ACM (17%). More specifically, the most attractive conference series for DM and SC appear to be ISC2 (23 articles), WAINA (8 articles), SMARTCOMP (8 articles), WF–IoT (8 articles), INFOCOM (8 articles) and UbiComp (7 articles).

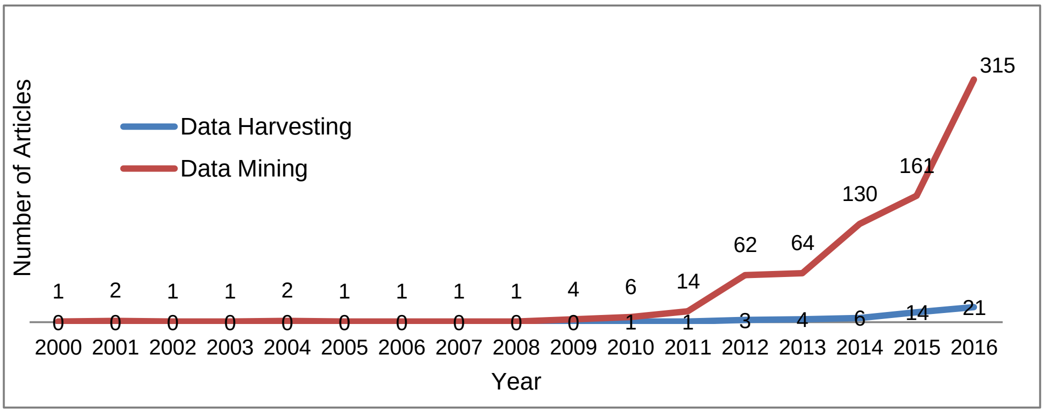
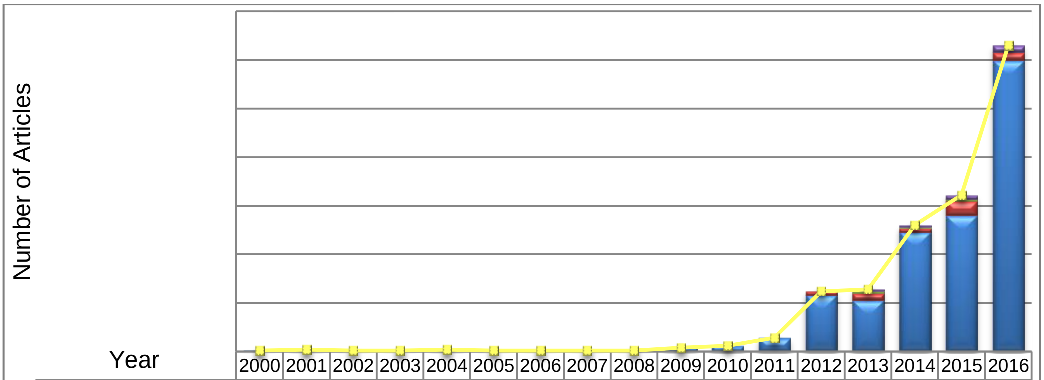
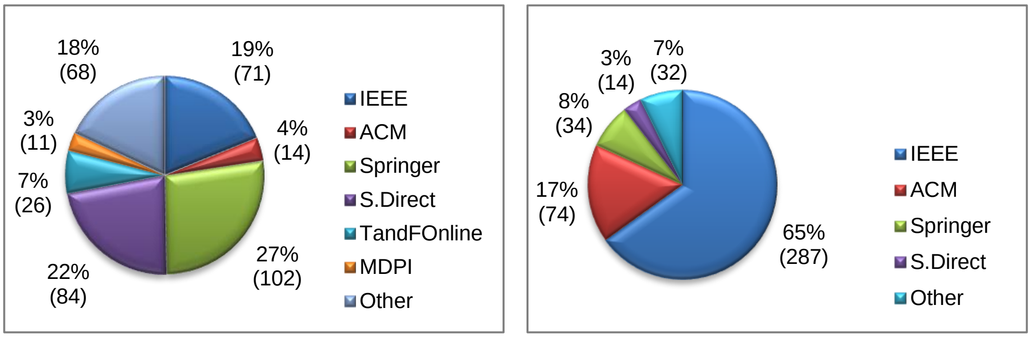


Fig. 5. Rate of published articles (yearly)



Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Science Direct														2	2	4	7
IEEE														2	1	2	
Scopus													4	7	4	15	8
Google Scholar	1	2	1	1	2	1	1	1	1	4	6	14	58	53	123	140	300
Total	1	2	1	1	2	1	1	1	1	4	6	14	62	64	130	161	315

Fig. 6. Number of published articles for «"Data Mining" AND "Smart Cities"» search term per digital library and per year



(a) Journal articles (b) Conference articles

Fig. 7. Proportions of articles per publication source in period 1996 – 2016

4.2 Qualitative Analysis

From the original sample and following Kitchenham's methodology, we came up with the selection and study of 204 articles. The *keywords* of the investigated articles were used for the creation of the tag cloud depicted in Fig. 8) in order to get a general overview of the review's outcomes [55–56]. The tag cloud illustrates the topics/terms where scholars pay attention in the domain of Data Science (DM and DH) and SC. Findings show that scholars are mostly interested in "IoT" and "smart mobility", while "crowd–sensing" and "smart living" are also topics of interest. Additionally, works appeared to focus on "open data", "big data","data mining", "Online Social Networks (OSN)", "smart governance", "smart environment", "smart people" and "cloud computing". The accurate results of the survey are presented in detail in Section 5.

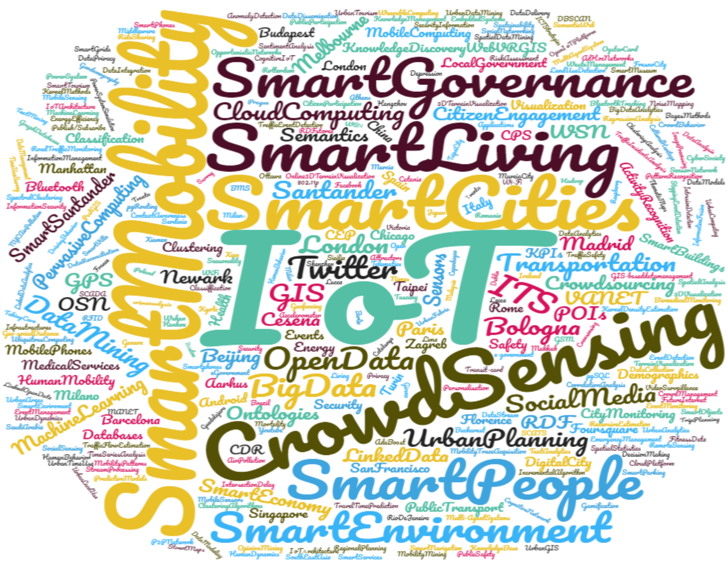


Fig. 8. Tag cloud of the investigated articles' keywords

The tag cloud (Fig. 8) depicts and highlights the intensity of such activities in specific cities, the majority of which coming from Europe: Santander, Aarhus, London, Copenhagen, Prague, Barcelona, Dublin, Madrid [57–60] and Italian cities (Rome, Cesena, Bologna, Florence, Lecce, Turin, Murcia, Trento) [61–66] appear as SC cases. Then, references appear for U.S. cities (Manhattan, Newark, NYC, Chicago, San Francisco) [67–69]. Asia follows, (Kyoto, Xian, Beijing, Taipei and Singapore) [70–73]. Finally, the city of Melbourne, Australia, has also been studied [74–75].

5. DISCUSSION: FROM SYSTEMATIC REVIEW TO TAXONOMIES

The thorough study of the 204 investigated articles and the synthesis of extracted data features (see Stage 2.4, Section 3) have led to the responses to the research questions (RQ2, RQ3, RQ4 and RQ5) raised in Section 3. The above systematic review and its results have offered the insight to proceed with further analysis in order to extend the systematic approach with a contextualized representation which would classify and order the involved data types, the methods, and the services offered in SC. Since taxonomies are a well comprehended and valuable tool for such a contextualization, it has been chosen as a "tool" to highlight knowledge and insights in terms of data production, sources devices, and analytics methods in the SC context. Thus, the effort for the systematic presentation of rich and significant outcomes of the review have driven the definition of taxonomies that will offer knowledge and insight in terms of urban data production and data processing and analysis methods in the context of SC. Each of the taxonomies was built according to the steps introduced by Bennett & Lehman [54], while it classifies and presents findings in a systematic and scalable manner. The novel "D", "M", and "S" taxonomies that concern individual taxonomies for data production, data analysis methods and smart services, respectively, return the unified "DMS" taxonomy. Each of "D", "M", "S" taxonomies corresponds to the components (data production, data analytics, services) of Fig. 2b which depicts the city as a "data engine".

The current Section is organized as follows: Subsection 5.1 outlines the findings that concern the urban data production in SC and answers to RQ4 and RQ5. Subsection 5.2 presents the DH and DM methods used so far to exploit urban data and answers to RQ2. Subsection 5.3 discusses the identified smart services and answers to RQ3. Subsection 5.4 completes Section 5, presenting three use case scenarios of "DMS" taxonomy highlighting its usefulness.

5.1 The "D Taxonomy": Urban Data Production

Literature review results contain important information that deal with urban data production (sources and types) and answer to RQ4 and RQ5. More specifically, according to the collection method (section 2.2.1) data sources can be distinguished in: i) *IoT* devices and ii) *crowd–sensing* processes. Results validated these classes (Fig. 9) and showed that IoT is the most usual source (42.6%), followed by crowd–sensing (22.05%). Nevertheless, both the sources can be combined in the urban context according to scholars (21.60%). On the other hand, some works claim to use "open data" (4.90%) as a data source, while the rest (8.80%) combine all the three data sources.

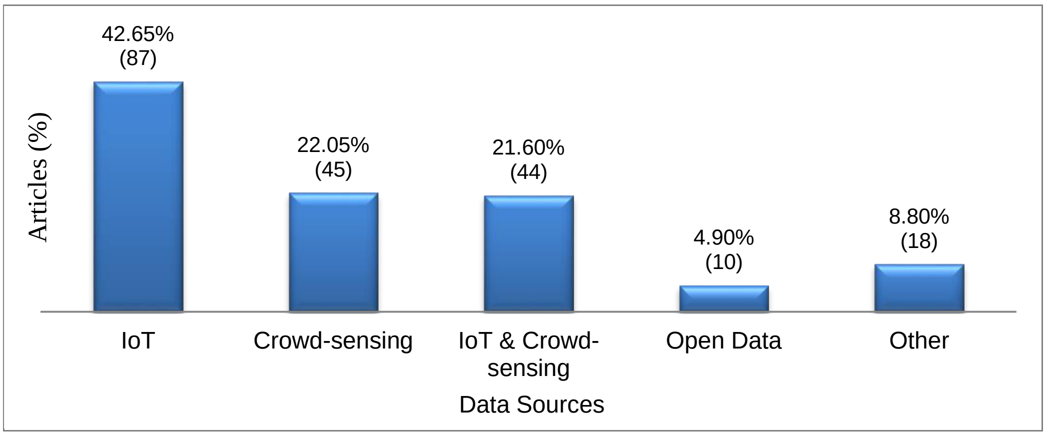


Fig. 9. Articles per data source

The study of the literature has shown that there is a rich variety of urban data sources that exhibit common features. Taking advantage of these features, we have developed the novel "D taxonomy" (Schema 1), which describes in a systematic manner all the sources of urban data and the types of data that were found. Each level of hierarchy in taxonomy is depicted in a different color, with the highest levels being more general and the lower the more specific. According to our taxonomy, the urban data may be raw data that comes directly from i) various devices, ii) network infrastructure, iii) applications, or be processed datasets that come from other data sources such as censuses, surveys, data providers or systems (ITS systems, GIS systems, etc.).

"D taxonomy" (Schema 1) attempts to describe the sources and the types of data that literature evidence provides. Different colors are used to depict each of the hierarchical levels in the taxonomy, with the highest levels being more generic and the lower more specific. Urban data may be *raw streams* that are collected directly from i) various devices, ii) network infrastructure, and iii) applications; or can be *processed datasets* that are collected from other sources such as censuses, surveys, data providers or information systems (e.g., Intelligent Transportation Systems (ITS), Geospatial Information Systems (GIS), etc.).

Collected data can be in *text, numbers, image, audio or video* format and can be accompanied by descriptive metadata. According to the type of data source, metadata concerns *time, measurements, records, unique attributes (ID, MAC address), social media data (posts, links, photos),* etc. Finally, collection can be continuous (systems and applications); periodical (sensors/actuators/RFID); or offline when (i.e., surveys, statistics, etc.).

Devices

Three types of data collection devices appeared in literature:

i. *Fixed,* which are located at specific places (e.g., buildings, streets, dumpsters, etc.) , and
ii. *Moving,* which are installed on a vehicle or other moving objects, or it is held by humans (e.g., mobile devices, wearing computing, etc.).
iii. *LiDAR (Light Detection And Ranging)* can be either static or moving [2], [60].

Fixed devices concern smart meters, sensors and actuators, cameras and Radiofrequency Identity (RFID) readers. They can be all used to sense, measure and record data with regard to mobility, environment and living SC dimensions [76–86].

On the other hand, moving devices offer flexibility and additional options. Mobile phones and tablets, wearable devices, Quick Response (QR) Codes and drones, as well as sensors, cameras and RFID tags –again– belong in this class [71], [87–91], [99].

Network Infrastructure

Network infrastructure interconnects devices and it is distinguished, again, in: i) *fixed* infrastructure and ii) *moving* infrastructure.

Fixed infrastructure is installed in specific places and concerns *Local Area Networks (LAN)* and *Wide Area Networks (WAN)* [92]; *Beacon networks* (RFID tags, NFC, etc.); and *wireless networks* (WiFi, 3G, 4G, etc.). They all enable citizens' interaction, social networking and transportation services, while they support urban planning and smart grid operation [93–96], [58].

Moving infrastructure on the other hand, concerns *Mobile Ad–Hoc Networks (MANET)* that are used for wide–scale urban monitoring [61]; and *Vehicle Mobile Networks (VANET)* that enable ITS deployment [62], [76], [97–98].

Applications

Cutting–edge ICT (e.g., Web 3.0, new programming languages, flexible data storages, powerful ICT tools, ubiquitous networks, etc.) have enabled the development of web and mobile applications, which provide the community and its stakeholders with visualized information and services within the urban space. Scholars in the analyzed literature introduced web platforms (e.g., Open Street Maps, Google Earth, Baidu, etc.) to visualize open data [91], [104] while others have developed web platforms (e.g. CAPIM platform, OpenIoT platform) for real–time processing and visualization of raw data by using cutting–edge data analysis tools [100–101]. As regards the mobile applications, some of these offer visualized information resulting from the processing of data [102], [113] while others are used as crowd–sensing applications [104–107]. Furthermore, social media (Foursquare, Twitter, Instagram, etc.) constitute an important urban data source, which in the absence of their users many times, used for recording of human activity and sentiment and opinion [63], [67–68], [108–109].

Other Data Sources

Several datasets can be also available and utilized within the context of a SC: historical data from surveys and interviews; statistical data with regard to local demographics and activities; processed datasets from service providers (e.g., city utility and telecommunications providers, energy suppliers, etc.) and information systems (e.g., ITS, GIS, etc.); and official reports (e.g., from local and national authorities, from the Organization of Economic Cooperation and Development (OECD), European organizations, etc.) are such datasets. Some corresponding examples come from Llacuna & Ibnez [110], who analyzed data from questionnaires for urban planning processes; Li et al. [111] examined the fiber–optic network in the city of Hankou with GIS data and tools; Calegari et al. [112] used several local and regional data sources in the city of Milan, Italy to recognize the emerging affinities; Balasubramani et al. [113] used datasets in the city of Chicago to help city administrators in decision making; while several scholars present cases, where data from heterogeneous sources were combined for interdisciplinary studies and for smart applications' development [114–119], [236–240].

5.2 The "M Taxonomy": Data Analysis Methods

DM and DH processes can follow different techniques and algorithms, which concern the "M Taxonomy" (Schema 2). The "M Taxonomy", which is depicted with the same coloring and hierarchy to the "D taxonomy", constitutes the answer to RQ2.

5.2.1 DH Pre–Processing

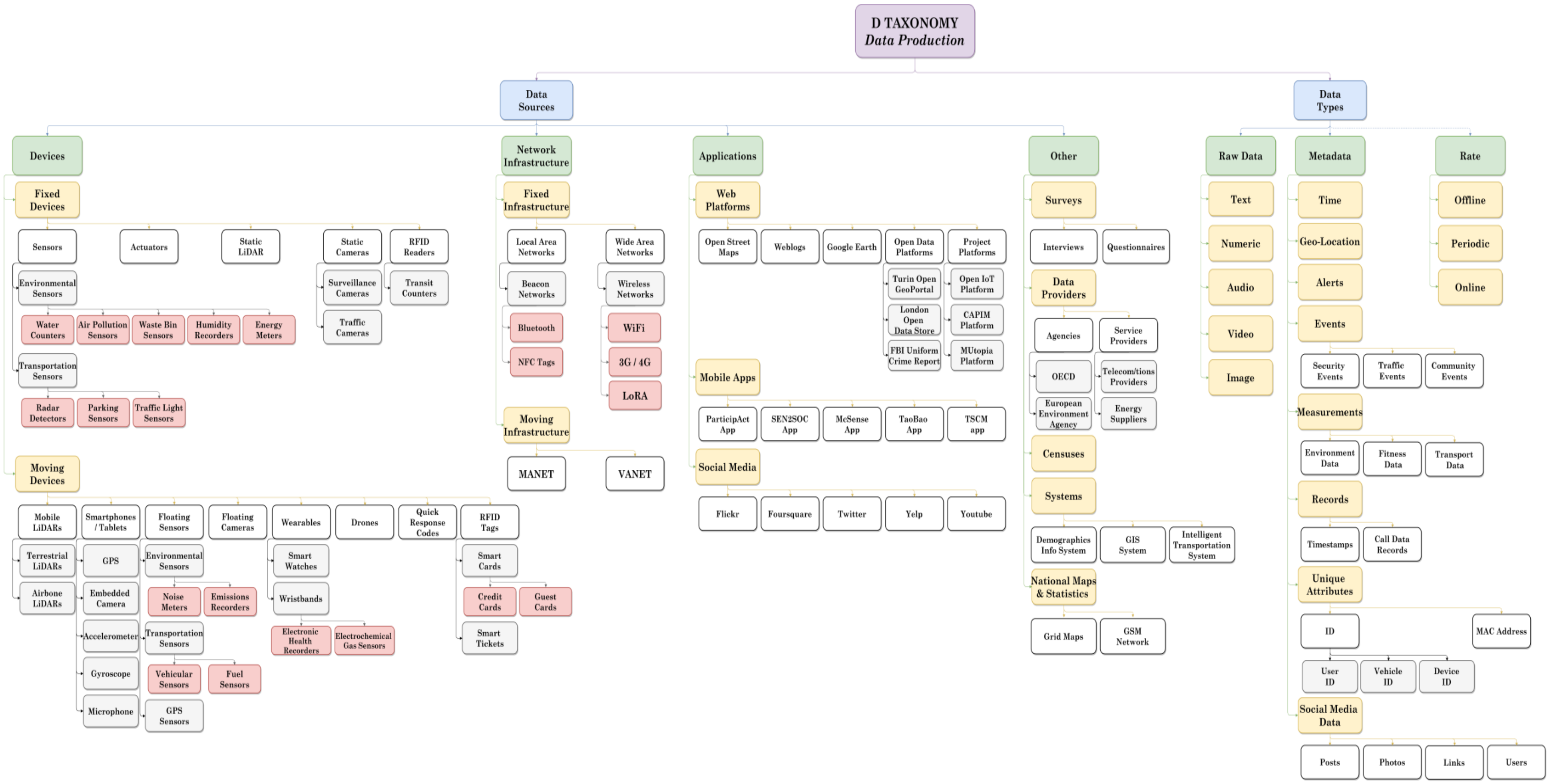
DH is usually being performed with the collection of data from various devices and with web scraping.

The collected data is being pre–processed for quality improvement purposes. Alternative pre–processing methods and techniques can be followed: *noise filtering*; *missing value filling*; *Principal Component Analysis (PCA)*; *data swapping*; *data interpolation*; *data discretization*; and *data compression techniques* can be applied on numerical data coming from various sensors [74], [120–124], [241]. Moreover, several techniques can be associated with *text data reduction (duplicates' removal and aggregation)*; *data cleaning (data annotation)*; and *data transformation (token filtering, out–of–words filtering, location filtering)* [119], [125–128], [242–244]. *Data reduction* and *integration techniques* can be applied to consolidate heterogeneous data from different data sources [2], [123], [129–130].

Literature evidence shows that structured data that is being retrieved from sensors, censuses, data providers or other sources is usually stored in *relational databases (SQL) (Microsoft SQL Server, PostgreSQL, Oracle Database and Sedna)*, while semi–structured and unstructured data from the Internet is stored in *non–relational databases (NoSQL) (MongoDB, HBase and CouchDB)* [62], [80], [103], [109], [131–136]. Data that describes ontologies and RDF (Resource Description Framework) graphs is usually stored in *Graph Databases (AllegroGraph, Apache Jena, Virtuoso, Oracle Spatial & Graph, Graph* DB and *Neo4j* [137–139]). In addition to traditional databases, *cloud databases* (i.e., Microsoft Azure®) are very popular since they provide scalability, flexibility and share ability, and are being used by a plethora of applications [75].

5.2.2 DM Pre–Processing & Processing

Several DM pre–processing and processing techniques and methods can be located and their usage ranges [40], [42], [44] according to the type and model of the data, the type of data store and the processing objectives. S*tatistical methods* and d*escriptive and predictive data mining techniques* are commonly used to exploit spatial, temporal or other numerical data such as measurements, coordinates, movements, recordings, call detail records, demographics, etc. Central tendency, dispersion measures and similarity measures are useful for investigating the characteristics and the similarities of the datasets; *Log Linear models* are suitable for the analysis of the relationship between categorical or quantitative variables [178], [195]; while *Linear Discriminant Analysis* and *Scale Linear Discriminant Analysis* are associated with classification problems [87], [162]. With regard to the descriptive DM techniques, many researchers have used clustering methods such as *Temporal Data Mining, Density–based Spatial Clustering, Partitional and Agglomerative Clustering* [63], [87], [90], [94], [112], [125], [134], [140–144], [245–246]. More specifically, *Symbolic Aggregate ApproXimation (SAX)* algorithm was used for the transformation of time–series into strings and *T–Density–based Clustering* algorithm *(T–DBSCAN)* was developed for the trajectory segmentation of GPS data [59], [145–146], [247]. Additionally, predictive DM techniques, such as *C4.5, RIPPER, CART* and *Naive Bayes* algorithms define a tree of options under decision–making purposes [79], [147–150].



Schema 1. The "D" Taxonomy outline

Similarly, many algorithms from the *Machine Learning* field can be utilized for DM, such as the *Latent Dirichlet Allocation* and the *Expectation Maximization* algorithms from Clustering techniques; the *k–Nearest Neighbor*, *Support Vector Machine* and *AdaBoost* algorithms from Classification techniques; and the *Apriori* algorithm from Association Rules [71], [86], [96], [108], [123–124], [162], [151–155], [248–251].

Apart from the traditional DM methods, advanced mining methods enable the exploitation of all types of heterogeneous data: *RDF graphs*, *ontologies*, *XML mining* and *social network mining* algorithms constitute valuable tools for the Semantic Web data analysis. Ontologies are used to organize knowledge and to explore relationships, while social network mining reveal the links between the actors define behavioral patterns [60], [140], [156–162], [252–253]. Text mining methods that were identified concern the *Centroid–fee Sequence algorithm* and *Maximum Entropy Classifier* [162].

Visualization methods and tools extract knowledge from urban data easily and quickly. *TensorFlow graphs* can be used for computation visualization; *tag clouds* for text visual representation; and *heat maps* for colorful, graphical representations [109], [133], [140], [163–165], [254].

Finally, some DM processing methods have been located in the fields of *Artificial Intelligence* (*Learning Real–time A* (LRTA*) algorithm*), *Fuzzy Logic* (*Genetic algorithms, Any Relational Clustering (ARCA) algorithm, FTI–*Apriori *algorithm*, *Gustafson–Kessel algorithm*) and *Artificial Neural Networks (Backpropagation algorithm)* [145], [166–169], [255–256].

5.3 The "S" Taxonomy: Smart Services

Smart services concern the "products/services" that the SC delivers to its stakeholders via its soft or hard facilities and aim to enhance the quality of life within a city, and in this respect to improve city's "livability" [1]. These services concern a "core element" of SC, since they support the realization of urban "intelligence" in terms of the SC six dimensions (people, economy, governance, environment, mobility and living) [1–2]. Literature findings (Fig. 10) demonstrate that the majority of the works are associated with smart mobility services (33.33%), followed by services that address a combination of SC dimensions (30.40%). In addition, 23 studies (11.30%) deal with smart living, while smart people, smart governance and smart environment dimensions have been discussed in 18 (8.83%), 17 (8.30%) and 15 (7.35%) articles respectively. Finally, only one article (0.49%) deals with smart economy dimension.

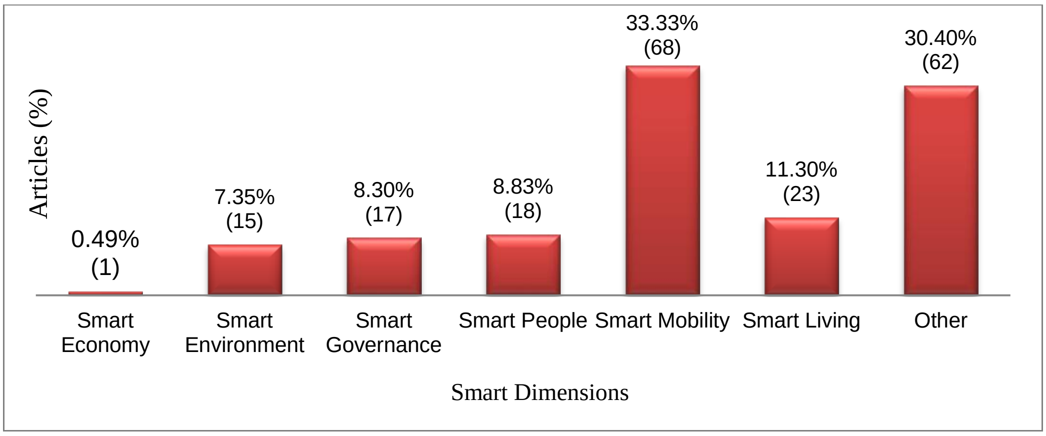
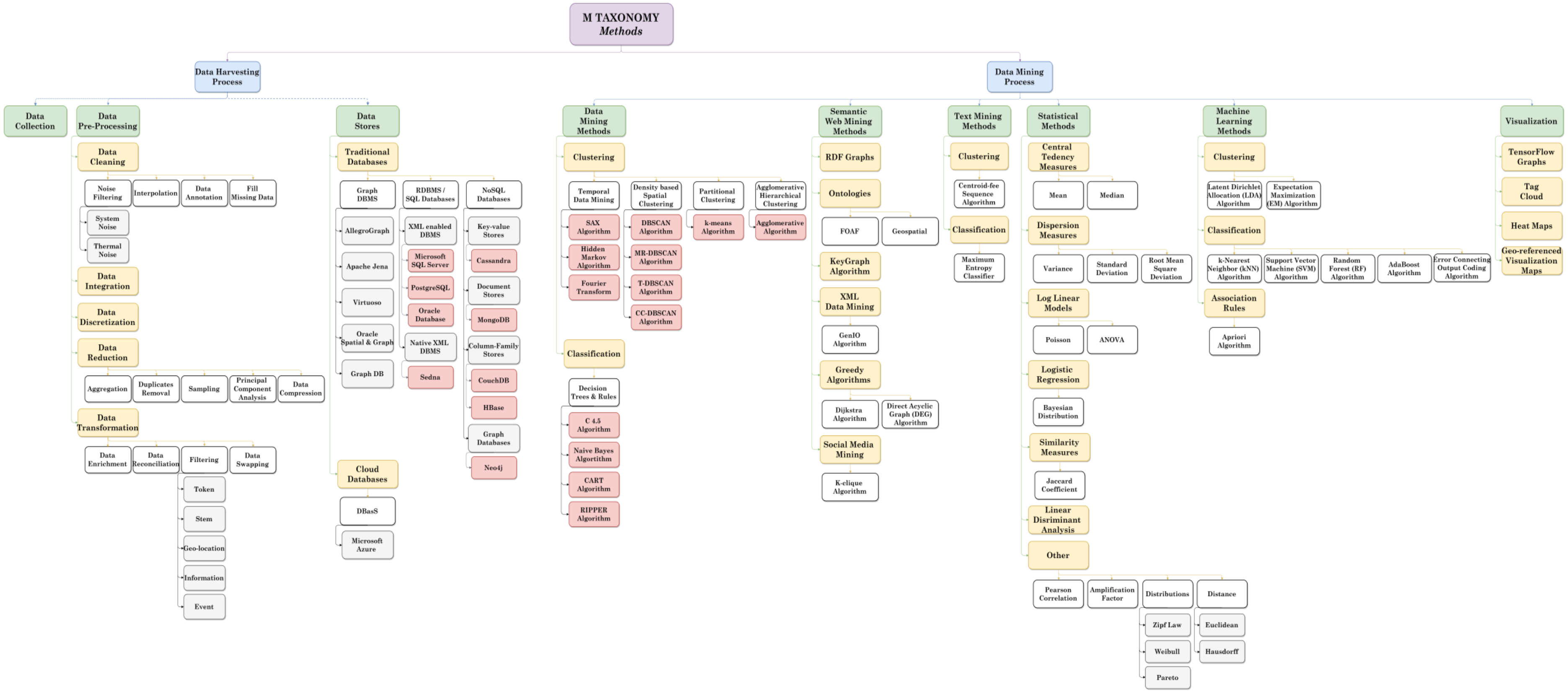


Fig.10. Articles per smart dimension

The identification and classification of all smart services by dimension, led to the deployment of the "S taxonomy" (Schema 3), which answers to RQ3.



Schema 2. The “M” Taxonomy outline

Smart Mobility

Urban requirements for safer, more efficient and sustainable mobility [170–171] have led to numerous innovative applications and systems for the estimation of trip duration, optimal route's identification and weather conditions' prediction [123], [134], [172–173], [257]; for public and personalized transportation information services [94], [142], [174–176], [258]. Additionally, city's traffic management concerns another challenge for the local governments and corresponding stakeholders [177], [100], [116], [259–260]. Furthermore, a lot of researchers have designed applications for car, ride and taxi sharing in order to improve traffic conditions and minimize costs and generated emission [64],[168],[178–179]. Finally, some applications deal with taxi services [88], [261] and flexible demand–oriented public pub services [145], [262].

Smart Environment

Pollution, climate change and sustainability are some environmental challenges that have been seen in the examined literature: real–time monitoring and management of public infrastructures, smart grids, smart buildings and smart lighting systems are some of the corresponding smart services [157], [180–181], [148], [263]. Furthermore, energy efficiency [182] and emission and waste monitoring and management [83], [160], [86], [183–184] are also of scholars' interest.

Smart Governance

Transparency and community's engagement can be enabled by ICT and corresponding services are seen from the government's perspective [1]. Open data portals, public consultations, service co–design and simplification and agencies' responsiveness [103], [164], [186–188] concern some of the corresponding smart services. Moreover, urban planning has been simplified from data analysis [70], [189–190], while crowd management and effective responses on emergency issues [108], [125], [165], [191] are of high interest too.

Smart People

This dimension deals with social and human capital including the level of qualification, participation and lifelong learning. Crowd–sensing is one of the identified data sources that can be utilized in this regard [107], [161], [192–195]. Additionally, co–creation and living labs [32], [196–197] can be also located as useful tools. Furthermore, community detection, human dynamics and behavior have also attracted scholars' attention [198–201]. Finally, Lenz et al. [202] have analyzed intelligent learning and evaluation mechanisms in schools and universities with wearable devices.

Smart Living

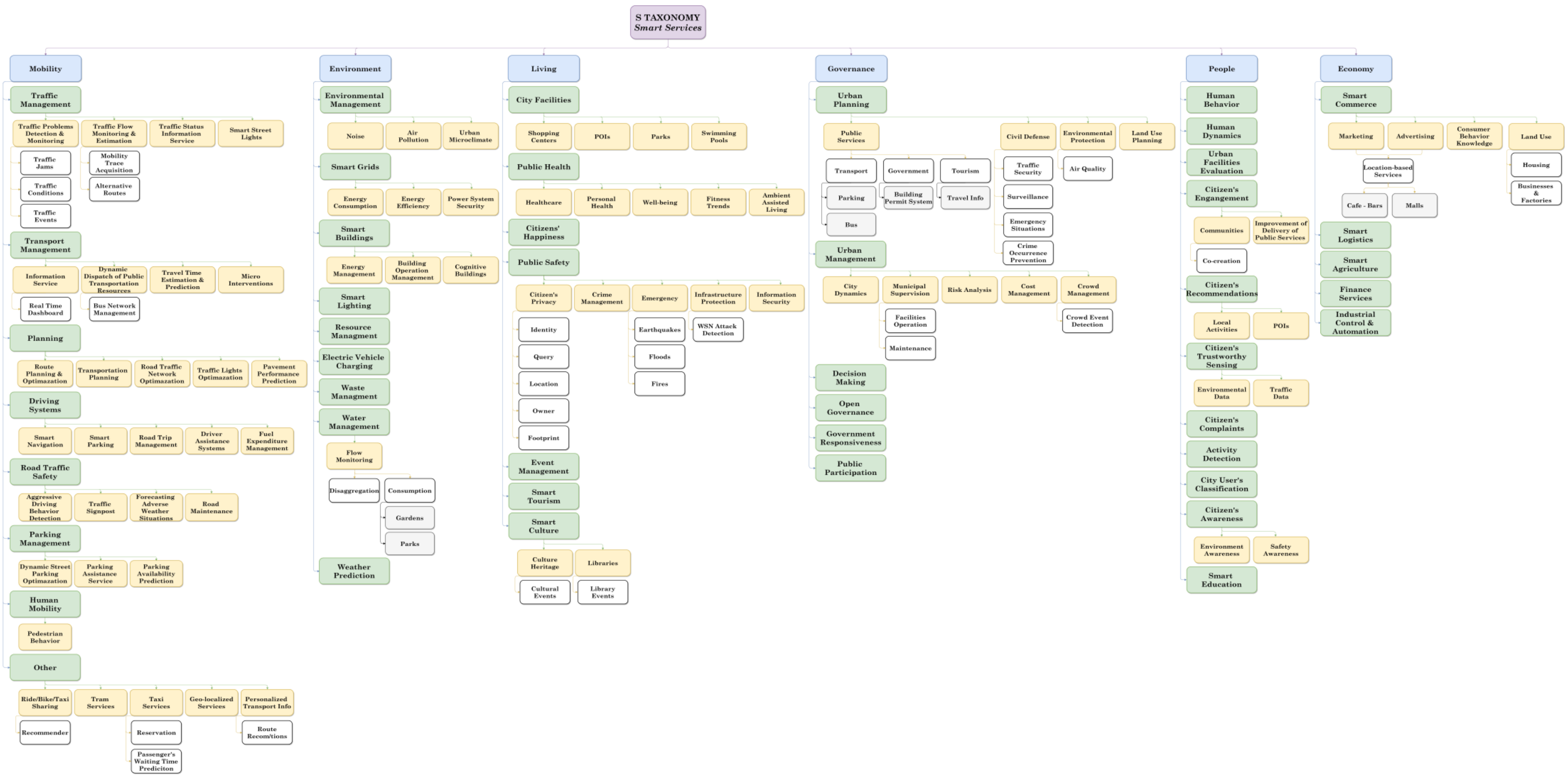
This class of services deal with urban facilities (e.g., parks, swimming pools, shopping centers, universities, etc.) [81], [150], [163], [203–204]; cultural events and activities, and touristic paths that make the city attractive to visitors and tourists [66], [205–206]; safety and emergency [122], [207–208]; and health and care [68], [79], [211–212].

Smart Economy

Smart economy addresses local growth and how it can be achieved based on the digital economy, entrepreneurship, flexibility of labor market, logistics, etc. [213–214].

Combination of Smart Services

DM and DH can be utilized for smart services that deal with more than one SC dimensions. For instance, transportation produce emission (NO_x, CO_2 PMs, etc.) that harms the environment [215–216] and affects the local quality of life and community's health [217–219]. On the other hand, public safety deals with smart living and smart governance [162], [220–221]. Furthermore, citizens' engagement is part of the smart people dimension but it is influenced by the openness of local governance. In this respect, several works combine more than one smart dimension [149], [222–223].



Schema 3. The “S” Taxonomy outline

5.4. Scenarios for Taxonomies Uptake

The proposed DMS taxonomy summarizes systematically the relevant literature of the previous years and aims to become a vital “tool” for stakeholders (i.e., researchers, developers, engineers, local authorities, etc.). The “DMS” taxonomy is scalable and offers the basis for classification of future work, in order to achieve better understanding of the emerging SC literature which scales up and evolves rapidly. Many use cases and scenarios can flourish based on the proposed taxonomy set as indicated next with three different indicative scenarios which exploit the unified DMS taxonomy set.

Use Case 1: Industrial domain exploitation
A Senior Engineer works in the company “X”, which is specialized in the fields of engineering design and prototyping, electronics, and communications and software solutions. Since the company participates in research projects, he is interested in proposing a new application for smart cities, which should be attractive and innovative to convince the project reviewers to fund it. Since he is responsible for submitting the proposal, he can use the “DMS” taxonomy to save time and effort. Starting with “S” taxonomy, he can easily identify which smart services have been developed so far, and depending on the project's objectives, he can decide on which dimension it will focus on. Considering that he chooses to develop an application for the environment –and in particular to control the quality of water in a lake– he can use the “D” taxonomy to identify which data sources have been used so far and which ones fit in his case. Then, after deciding to use fixed submerged measurement sensors, he has to discuss with the Software Engineer how they will collect, process and exploit the data that will be generated. The Software Engineer, in his turn, using the “D” and “M” taxonomies, can identify the type of generated data and decide which storage means and which methods of pre–processing and analysis are suitable for his purposes. The X’s work team, following the above simple procedure, combined with the use of the article that is more detailed, can easily design and implement the new application.

Use Case 2: Academia and scientific advancing
A PhD student and an early–stage researcher in the Department of Informatics with research interests regarding the study of intelligent cities in the light of the Data Science, with a careful reading of this article, can gain considerable insight into the subject of her dissertation, as it summarizes all the relevant bibliography concerning the years 1996–2017. She, using the “D”, “M” and “S” taxonomies, can easily understand how data is produced, processed and exploited in SC, as well as she can identify, directly, the research gaps. Also, she can exploit the literature was investigated in this article, and study in depth, depending on her interests, the urban data sources, the SC dimensions and services, as well as the urban data processing and analysis methods. Finally, she can identify publishers, journal and conferences related to her dissertation. Thus, she will save valuable time, her work will be facilitated, and she will focus on bridging the research gaps and addressing new challenges in SC era.

Use Case 3: Local Government Agency adoption
A technical advisor of C city's mayor and they have recently decided to take action to turn their city into a smart city. He, in collaboration with the Technical Services and the ICT department of the municipality, should examine the city's weaknesses and opportunities and propose smart services taking into account the existing infrastructure and implementation costs. He, by taking a look at “S” taxonomy, can get ideas for the smart services that have been developed so far to choose which ones fit in his case. Having decided on the service to be developed, he will discuss his idea with his colleagues, who can utilize the “D” and “M” taxonomies. The chief of technical services, utilizing the “D” taxonomy, will decide the choice of hard facilities (i.e. sensors, applications, networks, etc.), while the head of the ICT Department, utilizing the "M" taxonomy will choose the soft facilities (i.e. storage means, urban data processing and analytics methods, etc.). In this way, the municipal team, taking advantage of the unified "DMS" taxonomy, will be able to easily and successfully meet the mayor's expectations for a smart city.

6. ONGOING STATE –OF–THE–ART AND TRENDS

Since this systematic review covered literature analysis before the end of 2017, results of published work till the end of 2016 are summarized above, and the ongoing published work is presented here to indicate the current state of the art and its trends. The review of current year has identified ongoing scholars’ trends with regard to data and SC. The same keywords were used and the literature evidence that was published until December 2017, has followed the same process as above . Nevertheless, the outcomes were not incorporated directly in the previous analysis because many conferences were still under their publication process, while several journal articles delay with regard to their publication and/or even are published the following year. Despite their exclusion from the above analysis, literature findings of 2017 were examined with regard to publications’ number, focus and trends. Table 1 presents the corresponding findings, which show that publications kept on emerging during 2017 and doubled compared to 2016, a fact that validates the importance of this paper’s problem and an increasing scholars’ interest in data science and SC. The “screening” process of the articles followed the same inclusion/exclusion criteria that were followed before and left out articles irrelevant to the purposes of this study.

Table 1. Articles per resource

Resource	"data harvesting" AND "smart city"		"data mining" AND "smart city"	
	Initial results	*Articles after screening*	*Initial results*	*Articles after screening*
Google Scholar	44	24	1,330	548
Scopus	1	1	73	69
IEEE Xplore	0	0	27	10
Science Direct	4	4	17	11

The articles extracted for 2017 were examined in brief and not in the same detail as the publications from the past years of study but, some interesting findings were generated that are quite similar to the previous outcomes. More specifically, several journals from the same publishers appear to host corresponding works, while works with regard to DH/DM and SC were presented in some new conferences (e.g., ADHOC–NOW, MobileCloud, HealthINF, IISSC, IEEE International Conference on Smart City and SmartGreens, International Conference on Web Intelligence, Smart City Symposium Prague, International Smart Cities Conference, etc.). With regard to the context of the articles, scholars keep pay attention to similar types of data collection resources (IoT and crowd–sensing), while their works adjust to the generated DMS taxonomy. Only some new types of smart services were identified, which concern *smart food* [263] that belongs to smart living dimension; *transportation resilience* [264] that addresses smart mobility dimension; *energy usage patterns for load prediction* [265–266] that deals with smart environment and smart governance dimensions; *indoor space quality* it is related with smart buildings and it is measured by human behavior [267]; *crime prediction* via criminal behavioral analysis [268], which belongs to the context of safety in the smart living dimension. Scholars again, follow similar data collection methods, storage resources and analysis techniques/algorithms, facts that validate the accuracy of the identified DMS taxonomy. Big data and open data still attract scientific attention but, some new trends appeared from this brief analysis, which can be summarized on the following:

- There's an increasing *shift from SC smart dimensions to SC smart services:* more specifically, more and more scholars (i.e., [263], [264], [269–271], etc.) do not discuss the SC architectural dimensions and the corresponding indexes. Instead, they prefer discussing smart services (health, food, traffic, buildings, waste management, etc.) that are fed with DH and DM techniques.
- *Emerging topics appear* regarding *user behavioral analysis* (e.g., [272–277], [268], etc.) and *cyber–physical systems analysis* (e.g., [263], [278], etc.).

7. CONCLUSIONS

This paper dealt with SC analytics under the assumption of SC being a "data engine". Since data concerns one of the primary components of the SC architecture, which plays a significant role for SC to achieve in its mission, it is of high interest to understand how, where and why data is produced, collected, stored, processed, mined and visualized within the urban context. This problem is of high interest for both the Data Science and the SC domain, due to the emerging literature evidence with regard to data and SC. In this respect, this paper attempted to perform a comprehensive bibliographic analysis, which is missing from literature and that could connect the pieces between Data Science and SC. Due to the broad scope of Data Science, this paper focused on Data Harvesting and Data Mining in SC.

For the purposes of this review, the authors followed the Kitchenham [46] method: the authors defined broadly accepted bibliographic resources, which were crawled with relative keywords for an extensive time period (1996–2016), while even articles from the ongoing 2017 were collected. A screening process left out irrelevant works and a detailed study of the remaining articles was performed. The overall process attempted to provide with answers 5 research questions (RQ1–RQ5), which were relative to the purposes of this article. Results show that an emerging number of articles has been published (Fig. 5) since the initial appearance of SC in literature, while more attention is paid on DM instead of DH in the urban context (RQ1). Due to the broad context of the identified evidence, the remaining research questions (RQ2–RQ5) have been answered with an identified taxonomy ("DMS"). This taxonomy demonstrates a broad sources and types of storages for the generated urban data (RQ4), which mainly deal with IoT and crowd–sensing. Quite often, these two sources are combined in order to obtain more data which are complementary or interrelated. Of course, the proliferation of smartphones, wearable devices and the development of mobile applications have contributed decisively to the spread of crowd–sensing. On the contrary, open data, despite the efforts made to promote them, are scarcely used. Additionally, several collection/storing/mining methods appear to be preferred by scholars (RQ2), while even more are under investigation.

With regard to the collection and analysis of urban data, our research has revealed that an effort is being made for the real–time collection, processing and analysis of urban data to allow immediate monitoring of life in cities and facilitate the decision making. In this respect, urban data is collected and exploited using conventional DH and DM methods and techniques. The deployment and use of NoSQL and cloud databases, and the multi–purpose open source tools (Apache Hadoop, TensorFlow Graphs, etc.) offer flexibility and facilitate the processing and analysis of this data. Apart from the traditional DM methods, advanced DM methods such as text mining and web mining, as well as methods from other fields such as statistics, machine learning, visualization, fuzzy logic, artificial neural networks are used.

A continuous shift from SC smart dimensions to SC smart services appear in literature, which keeps evolving in 2017, while all types of services are fed with collected data with a preference to transportation, health, safety/emergency and environmental services (RQ3). Finally, emerging smart applications utilize and visualize open and big data that are being produced by sensors or via users (crowd–sensing) in SC (RQ5), while trends show preference to applications that analyze human behavior for several purposes (e.g., environment, mobility, consuming, etc.).

Classifying the smart services, which have been developed so far, in the six proposed dimensions of smart cities proposed by Giffinger & Gudrun [10], it turned out that up to now particular attention was placed mainly on the smart mobility and smart living dimensions. In the smart mobility case, an abundance of services have been developed due to the many local authorities initiatives. In such intitiatives, emphasis has been placed on smart mobility which largely facilitates transport and leads to saving time and enhance city's energy efficiency (e.g., fuels, road maintenance costs, etc.), combined with the relative ease of collecting mobility data (e.g., transfer cards, fixed devices on roads, etc.). The multifaceted dimension of smart living has attracted the interest of both the public and the private sector. Several applications have already been developed in the context of smart living, which emerge and evolve because human needs and city trends are dynamic and unforeseen so there are still several services to be developed. In the smart governance, smart people and smart environment dimensions, several services have also been deployed, but enhancements are still expected with future services i.e. the ones dealing with self–service government, "we–government" [1], etc. Finally, our results have shown that few studies and smart services are related to the smart economy dimension. This deficiency may be due to the fact that this dimension is associated with companies that do not disclose their business data, while the entire data–economy can be considered that it concerns this SC dimension. A long with previous findings, our survey has revealed that there is a tendency to combine smart dimensions in the study and development of smart services. This is justified because dimensions are inextricably linked and interact with each other.

Some additional outcomes have been extracted from this study: most case studies in existing literature can be located in Europe, while North America and Asia follows. This finding may validate the continuous political support that SC gains momentum in Europe, which can be justified by corresponding policies and funding opportunities (i.e., Horizon 2020, URBACT, etc.). On the other hand, the wide context of methods and techniques for Data Harvesting (DH) and Data Mining (DM), is further being encouraged by the recent trends for cyber–physical systems and human behavioral analysis, while it leaves space for corresponding products' standardization.

The double size of the publications that have been located in 2017 generates a limitation for this paper's findings, while it grounds a necessity for continuous update of the "DMS taxonomy". On the other hand, this emerging amount of corresponding publications justifies the importance of this paper's findings and of the "DMS" contribution, since it can play the role of a "roadmap" for researchers and practitioners who work in the domains of Data Science and SC. A further limitation is that our findings resulted from the exploitation of the Kitchenham's methodology and the use of specific search terms selected according to the purpose of the current systematic review. The findings will certainly be different in cases where: i) a different research approach or methodology is adopted; ii) different search terms are selected; and / or iii) different inclusion/exclusion criteria are set.

Beyond the role of the identified "DMS" to this study, the generated taxonomy offers significant potentials to forthcoming scientific works: scholars can follow the traces that have already been defined and even tested in several cities around the world in order to go beyond existing state–of–the–art in terms of DH, DM and SC. In this respect, this work's results can be utilized for future works that will be performed by scholars who work in Data Science and SC. Some more future thoughts concern the continuous update of "DMS" with the incorporation of detailed analysis even from 2017. Nevertheless, the emerging amount of corresponding publications (articles in 2017 are double the size of the ones in 2016), makes this future process quite hard to be performed and the existence of "DMS" to be very important. Due to the extensibility and flexibility of "DMS" taxonomy, each stakeholder (e.g., researcher, developer, etc.), will be able to classify his/her work into the existing categories of "DMS" or to add new categories (and subcategories), concerning new sources and analysis methods of urban data and smart services. Thus, the "DMS" will be constantly updated, the bibliography will continue to be ordered and the research gaps will be recognized quickly facilitating further research. Some future thoughts of this study concern the continuous update of the taxonomies, as well as the testing with regard to the alignment of the identified SC data utilization scenarios to these taxonomies. Moreover, trends like Complex Systems Science on SC can be also investigated on the extracted outcomes with regard to SC dimensions and services.

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