

A Systematic Review for Smart City Data Analytics

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Smart cities (SCs) are becoming highly sophisticated ecosystems at which innovative solutions and smart services are being deployed. These ecosystems consider SCs as data production and sharing engines, setting new challenges for building effective SC architectures and novel services. The aim of this article 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 particular, 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: • **Information systems** → **Data analytics**; • **Human-centered computing** → *Collaborative and social computing*; • **Applied computing** → *Enterprise ontologies, taxonomies and vocabularies*; • **Computing methodologies**;

Additional key words and phrases: 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 (SCs) have changed radically since the initial appearance of the term in literature in the late 1990s due to the impact of disruptive technologies and new forms of interaction in everyday life. Multiple stakeholders act in parallel with joint forces of governments, industries, and scientists

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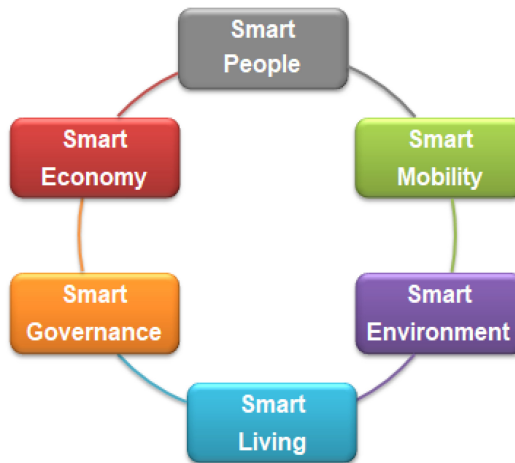


Fig. 1. The six dimensions of SCs.

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 Institute³) 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 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 Ericsson⁸) define a new competitive market that is estimated to become dominant by 2030 [1], while *scientists* investigate the future of an interdisciplinary and very promising domain that combines studies like engineering, ICT, humanities, ethics, political science, and so on.

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]) provide alternative definitions, conceptual models, and architectures for SCs, 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 SC conceptual framework analyzes the SC in six dimensions, in an attempt to define indexes that can measure urban intelligence (Figure 1) [10]: (i) *smart economy*, (ii) *smart mobility*, (iii) *smart environment*, (iv) *smart people*, (v) *smart living*, and (vi) *smart governance*.

Since SCs 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

¹<http://ec.europa.eu/eip/smartcities/>.

²<http://www.worldsmartcity.org/>.

³<http://www.smartcibi.org/>.

⁴<https://sustainabledevelopment.un.org/post2015/transformingourworld>.

⁵<http://www.cisco.com/c/en/us/solutions/industries/smart-connected-communities.html>.

⁶http://www.ibm.com/smarterplanet/us/en/smarter_cities/overview/.

⁷http://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>.

services to and from local stakeholders [11]. These services range from upgraded typical city utility services (i.e., water, energy, gas) 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). SCs 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.

In 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 particular, 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 [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) and on new technologies (e.g., smart cars, smartphones), 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 [26] has revealed that there are 4.9 billion connected objects, which are expected to reach or exceed 50 billion in 2020 and over 1.4 billion smartphones, while the market of Radio Frequency Identification (RFID) tags is worth \$11.1 billion and 500 million vehicles are expected to be connected to the Internet by 2020. Specifically, according to Statista,¹¹ 1.8 billion connected objects were within SCs 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 data offering unlimited opportunities for gaining profound insights into the cities of today and knowledge out of them is not yet fully exploited, as this data is often scattered or unavailable [27]. 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 SCs, 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 [28]. 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 refer to data and SC, a systematic analysis which connects the “pieces” between Data Science and SCs is still missing. The current article is

¹⁰<https://www.postscapes.com/anatomy-of-a-smart-city/>.

¹¹<https://www.statista.com/statistics/422886/smart-cities-connected-things-installed-base/>.

a comprehensive survey which examines the way in which urban data are used in SCs, 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 revealed 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, emerge. 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 remainder of this article is organized as follows: Section 2 discusses the theoretical background and highlights this article’s objectives with an 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 the 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, 29, 30] 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 sets of smart services. Furthermore, British Standard Institution (BSI) [30] views SC as a system that consists of several subsystems (so-called “infrastructure-based” and “service-based” sectors) (Figure 2(a)), 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 (Figure 2(b)) and explained in the following subsections, where city appears as “data engine” and dataflows 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.

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. Section 2.1 refers to the production of urban data and its features, while Section 2.2 involves the data analytics basics, focusing mainly on the “Data Harvesting” and “Data Mining” processes.

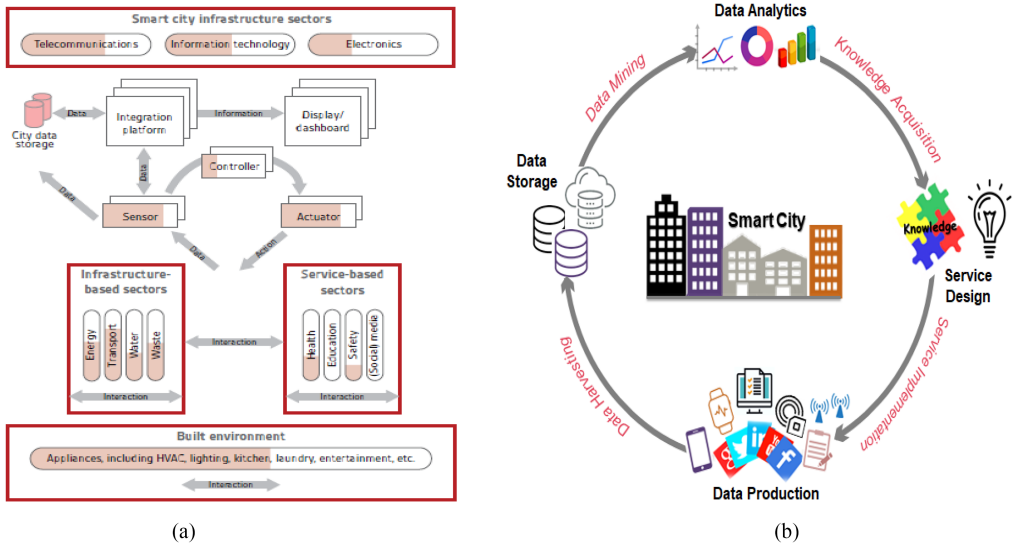


Fig. 2. (a) City as a “data system” [30], (b) Smart city as a “data engine.”

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 a large scale of heterogeneous datasets. Urban data is produced either directly during daily activities and smart service execution (e.g., social networks, smart applications) 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). The differentiation of SC data sources typically involves two major data origin levels [1]:

- IoT data production from sensors and actuators embedded in physical objects which are linked through wired and wireless networks [31]. This “umbrella” term involves all the interconnected smart devices, such as RFID tags, sensors, cameras, mobile devices, Near Field Communication (NFC), and so on.
- 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 [32]. 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 to as Mobile Crowd-Sensing and Computing (MCSC) [33]. Crowd-sensing has largely contributed in the definition of the so-called Internet of People (IoP) [34], 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 [35].

Data derived from the urban data sources is characterized by heterogeneity and it typically is of big data scale, based on the Gartner [36] 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 [37] big data definition which identifies the five big data characteristics, known as the 5V’s which are (i) volume, (ii) variety, (iii) velocity, (iv) veracity, and (v) value. This is due to the

SC typical sources such 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 [38]. 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). Shared data is published with the name of its owner (e.g., published surveys, social media data). In case data is accessible and available for everyone to acquire, use, and process without restriction by copyright, it is called *Open Data* [39]. 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 Commission¹⁶ 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 Organicity²⁰).

2.2 Data Analytics Basics

Data production in SC sets new challenges when it comes to revealing patterns and detecting norms and phenomena in the city context. SC data analytics is an important approach toward 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 Figure 2(b), 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*” [40]. 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 datasets. Urban *raw data* is characterized by heterogeneity (different types, duration, format), while it may contain noise and be inaccurate [41]. The *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* [42]. Then, depending on the portability and usability requirements, the pre-processed datasets 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 [43–45]. 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) are crucial for the acquirement and management of high-quality datasets that will facilitate the data analysis and offer worthwhile and accurate insights [46, 47].

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/>.

According to Kantardzic [48], “*Data Mining is a process of discovering various models, summaries and derived values from a given collection of data.*” The 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 others [48]. 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), as well as to predict and prevent future situations (e.g., resource management, delinquent behavior prevention) [46].

“*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 types 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, and so on are implemented to gain knowledge and to advance SC intelligence detection [49]. 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 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 a 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 [50, 51]. 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 [52]. This method is chosen since it follows a uniform protocol, which unfolds in *three phases* with the following specific stages (outlined in Figure 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; and

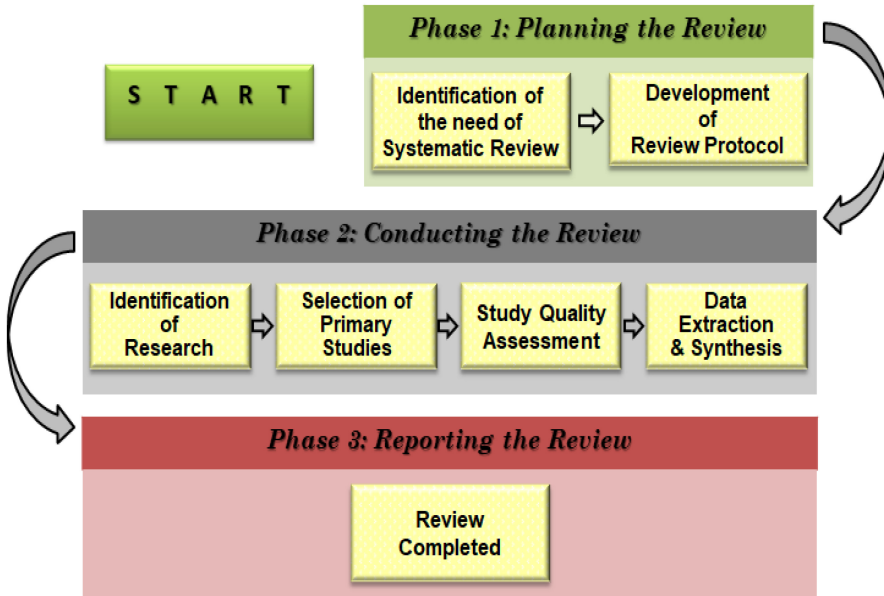


Fig. 3. The phases of the systematic review process.

(iii) the *Reporting Phase*, to deliver an overall presentation and the peer review of the systematic review.

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 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 SCs);
- (ii) the *Interventions* that addresses the alternative approaches and methods to the topic and/or their comparison (e.g., data analytics methods, smart services); and
- (iii) the *Outcomes* that reflect results and factors, which can be used for the interventions' comparison (e.g., algorithms, smart applications).

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 following 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 [53]. 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 [54–56]: *Google Scholar*,²¹ *Scopus*,²² *IEEE Xplore*,²³ and *Science Direct*.²⁴ According to Brophy and Bawden [57], 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

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/>.

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 and Angelis [53], who have explained, in their work, that “the determination of search terms is an iterative procedure starting with trial searches using different search terms, 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 [57, 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 which 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 which correspond to at least three articles from those 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 SCs.

– ***Exclusion Criteria***

- (1) Articles performing studies related to smart services and not to SCs.
- (2) Articles performing studies referring only to data harvesting/data mining processes or only to SCs.

Stage 2.3: Study Quality Assessment

According to Kitchenham [50], the Quality Assessment of articles is very difficult and depends on various factors. The adoption of additional criteria is needed to make certain of 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 the following:

- (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);
- (ii) *the availability of the data*, i.e., information on access to aforementioned used data (e.g., URLs, DOI, databases, organizations that provide data);
- (iii) *the description of the used methodology*, (i.e., detailed description and documentation of the methodology steps by citing fundamental axioms, rules);
- (iv) *the presentation of the results* (i.e., comprehensive and coherent presentation using graphs, tables).

Stage 2.4: Data Extraction and Synthesis

During this last stage, valuable information is extracted from the final sample of articles, which remained after “screening” and can provide answers to 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

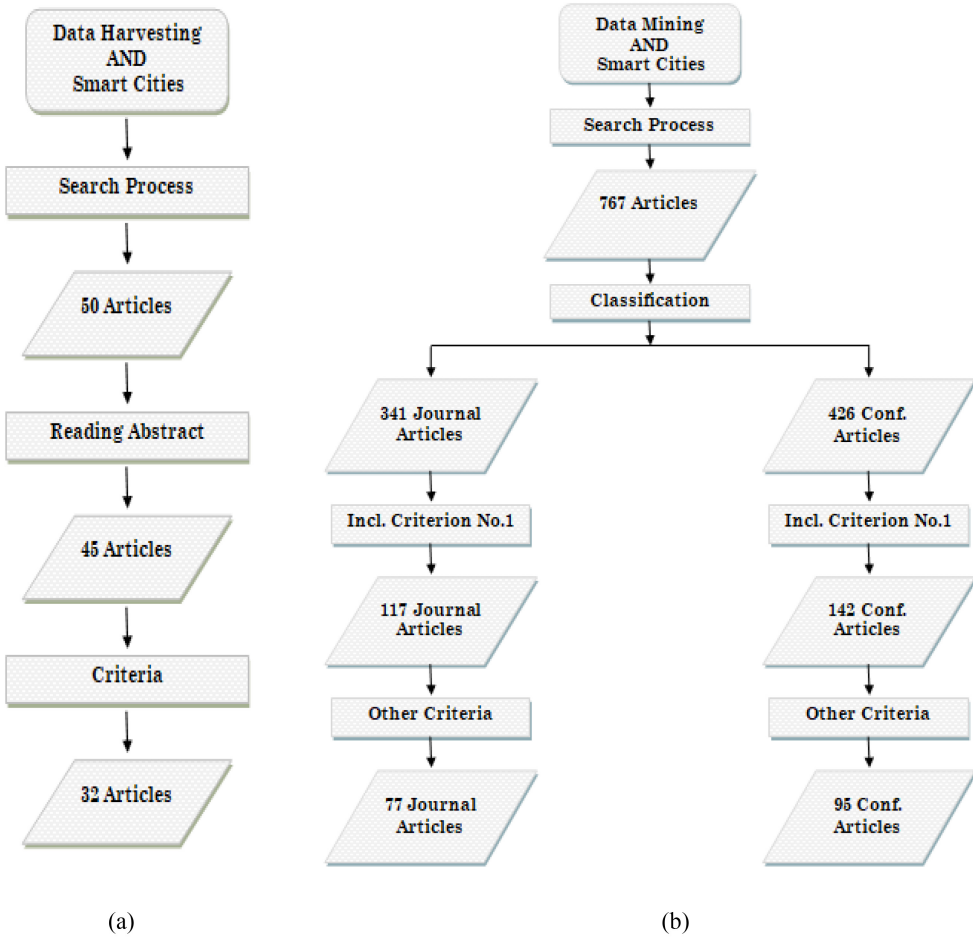


Fig. 4. Selection process of the articles final sample.

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) SC dimensions and SC 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 Figure 4.

With regard to “Data Harvesting AND Smart City,” 50 candidate articles were found, by performing the initial search process (Figure 4(a)). The “screening” process left out five irrelevant articles. After studying the remaining articles, 13 more were removed as irrelevant based on the

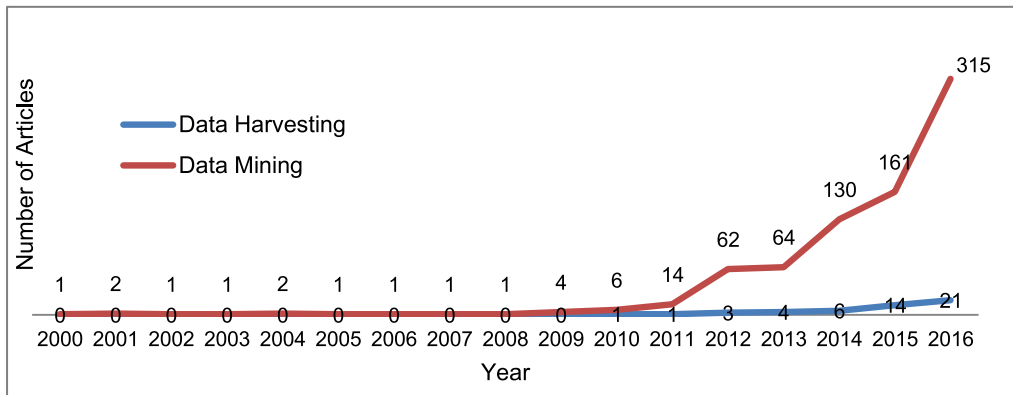


Fig. 5. Rate of published articles (yearly).

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 (Figure 4(b)). This set was classified according to the publication type in *Journal Articles* (341) and *Conference Articles* (426). The *Inclusion Criterion 1* resulted in 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.

The data features derived from the remaining set of articles and their synthesis are presented in detail in the Sections 4 and 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. Section 4.1 summarizes the initial sample of articles and answers to RQ1, which concerns the number of articles addressed to data harvesting and data mining processes, while Section 4.2 offers a general overview of the outcomes of the investigated articles.

4.1 Quantitative Analysis

Results to the response to RQ1 are depicted in Figure 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 regard 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

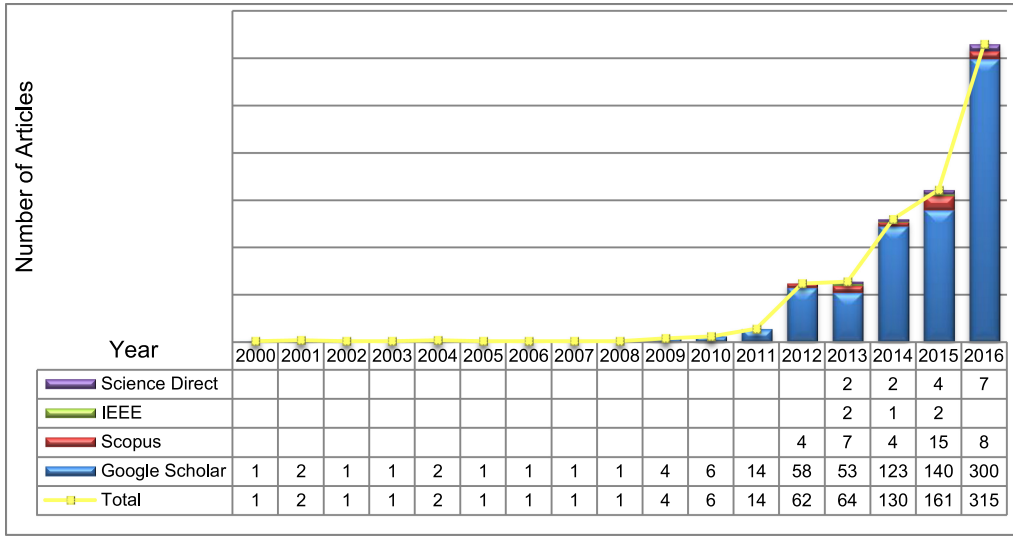


Fig. 6. Number of published articles for «“Data Mining” AND “Smart Cities”» search term per digital library and per year.

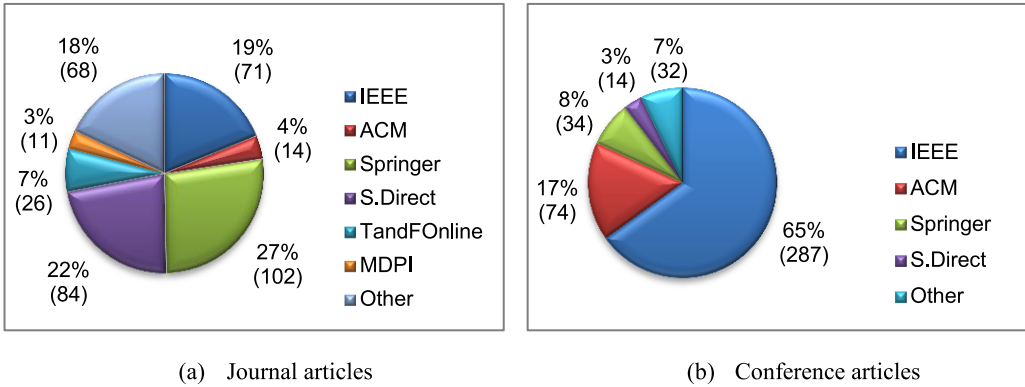


Fig. 7. Proportions of articles per publication source in period 1996–2016.

the articles were collected from Google Scholar® (92.5%), while Scopus® (4.95%), Science Direct® (1.95%), and IEEE Explorer® (0.65%) follow (Figure 6). With regard to corresponding publishers (Figure 7(a)), Springer journals have published the majority of articles (27%) followed by Elsevier (22%) and IEEE (19%). On the other hand (Figure 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).

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 Figure 8 in order to get a general overview of the review’s outcomes [58, 59]. The tag cloud illustrates the topics/terms where scholars pay attention in the domain of

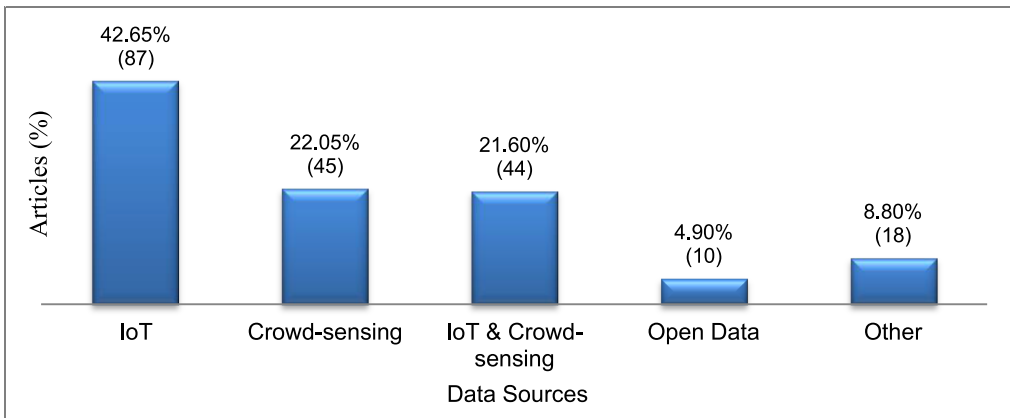


Fig. 9. Articles per data source.

taxonomy. Each of “D,” “M,” and “S” taxonomies corresponds to the components (data production, data analytics, services) of Figure 2(b) which depicts the city as a “data engine.”

The current section is organized as follows: Section 5.1 outlines the findings that concern the urban data production in SC and answers to RQ4 and RQ5. Section 5.2 presents the DH and DM methods used so far to exploit urban data and answers to RQ2. Section 5.3 discusses the identified smart services and answers to RQ3. Section 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 deals with urban data production (sources and types) and answers 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 (Figure 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 three data sources.

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 can be processed datasets that come from other data sources such as censuses, surveys, data providers, or systems (ITS systems, Geospatial Information 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., ITS, GIS).

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)*, and so on. Finally, collection can be continuous (systems and applications); periodical (sensors/actuators/RFID); or offline (i.e., surveys, statistics).

Devices

Three types of data collection devices appeared in literature:

- (i) *Fixed*, which are located at specific places (e.g., buildings, streets, dumpsters), 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).
- (iii) *LiDAR (Light Detection And Ranging)* can be either static or moving [2, 63].

Fixed devices concern smart meters, sensors and actuators, cameras, and Radiofrequency Identity (RFID) readers. They can all be used to sense, measure, and record data with regard to mobility, environment, and living SC dimensions [79–89].

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 [74, 90–94, 95].

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)* [96]; *Beacon networks* (RFID tags, NFC, etc.) [97–99]; and *wireless networks* (WiFi, 3G, 4G, etc.) [100, 101]. They all enable citizens' interaction, social networking, and transportation services, while they support urban planning and smart grid operation [102, 103, 61].

Moving infrastructure, on the other hand, concerns *Mobile Ad-Hoc Networks (MANET)* that are used for wide-scale urban monitoring [64], and *Vehicle Mobile Networks (VANET)* that enable ITS deployment [65, 79, 104, 105].

Applications

Cutting-edge ICT (e.g., Web 3.0, new programming languages, flexible data storages, powerful ICT tools, ubiquitous networks) 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) to visualize open data [94, 106–108] 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 [109, 110]. As regards the mobile applications, some of these offer visualized information resulting from the processing of data [111, 112] while others are used as crowd-sensing applications [107, 113–116]. 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 [66, 70, 71, 117, 118].

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) and information systems (e.g., ITS, GIS); and official reports (e.g., from local and national

authorities, from the Organization of Economic Cooperation and Development (OECD), European organizations) are such datasets [119–123]. Some corresponding examples come from Llacuna and Ibnez [124], who analyzed data from questionnaires for urban planning processes; Li et al. [125] examined the fiber-optic network in the city of Hankou with GIS data and tools; Calegari et al. [126] used several local and regional data sources in the city of Milan, Italy to recognize the emerging affinities; Balasubramani et al. [108] 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 [127–140].

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 as 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 [77, 141–146]. 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)* [99, 132, 147–152]. *Data reduction and integration techniques* can be applied to consolidate heterogeneous data from different data sources [2, 144, 153–155].

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*) [65, 83, 108, 118, 156–161]. Data that describes ontologies and RDF (Resource Description Framework) graphs is usually stored in *Graph Databases* (*AllegroGraph, Apache Jena, Virtuoso, Oracle Spatial and Graph, Graph DB, and Neo4j* [162–164]). 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 [78].

5.2.2 DM Pre-Processing and Processing. Several DM pre-processing and processing techniques and methods can be located and their usage ranges [42, 44, 48] according to the type and model of the data, the type of data store, and the processing objectives. *Statistical methods and descriptive 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, and so on. 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 [165, 166]; while *Linear Discriminant Analysis* and *Scale Linear Discriminant Analysis* are associated with classification problems [90, 167]. With regard to the descriptive DM techniques, many researchers have used clustering methods such as *Temporal Data Mining, Density-based Spatial Clustering, and Partitional and Agglomerative Clustering* [66, 90, 93, 98, 126, 147, 159, 168–174]. More specifically, the *Symbolic Aggregate ApproXimation (SAX)* algorithm was used for the transformation of time-series into strings and the *T-Density-based Clustering* algorithm (*T-DBSCAN*) was developed for the trajectory segmentation of GPS data [62, 175–177]. Additionally, predictive DM techniques, such as

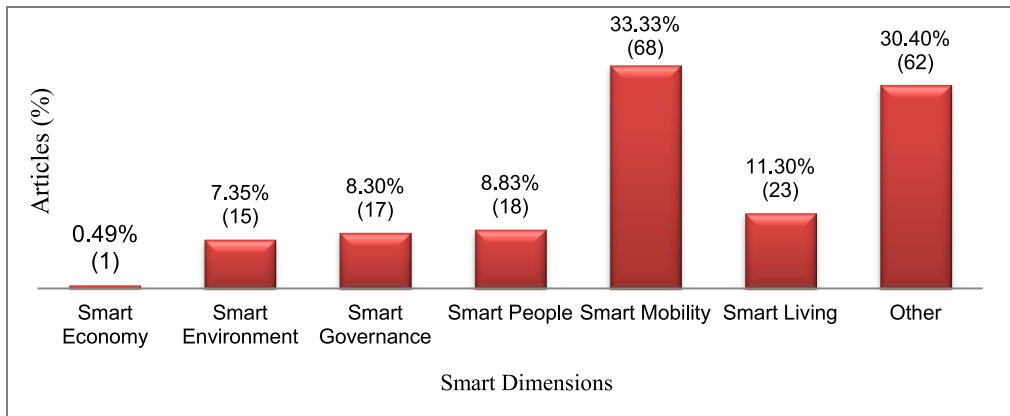


Fig. 10. Articles per smart dimension.

C4.5, *RIPPER*, *CART*, and *Naive Bayes* algorithms define a tree of options under decision-making purposes [82, 178–181].

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 [74, 89, 97, 103, 117, 144, 145, 182–189].

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 reveals the links between the actors define behavioral patterns [63, 168, 191–199]. Text mining methods that were identified concern the *Centroid-fee Sequence algorithm* and *Maximum Entropy Classifier* [197].

Visualization methods and tools extract knowledge from urban data easily and quickly. *Tensor-Flow graphs* can be used for computation visualization; *tag clouds* for text visual representation; and *heat maps* for colorful, graphical representations [118, 158, 168, 200–203].

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*) [175, 204–209].

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 (Figure 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.

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

Smart Mobility

Urban requirements for safer, more efficient, and sustainable mobility [210, 211] have led to numerous innovative applications and systems for the estimation of trip duration, optimal route’s identification, and weather conditions’ prediction [144, 159, 212–214], and for public and personalized transportation information services [98, 170, 215–218]. Additionally, city’s traffic management concerns another challenge for the local governments and corresponding stakeholders [109, 129, 219–221]. 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 [67, 208, 222, 223]. Finally, some applications deal with taxi services [91, 224] and flexible demand-oriented public services [175, 225].

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 [179, 192, 226–228]. Furthermore, energy efficiency [229] and emission and waste monitoring and management [86, 89, 195, 230, 231] 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 [108, 201, 232–234] concern some of the corresponding smart services. Moreover, urban planning has been simplified from data analysis [73, 235, 236], while crowd management and effective responses on emergency issues [117, 147, 202, 237] 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 [113, 196, 238–241]. Additionally, co-creation and living labs [35, 242, 243] can be also located as useful tools. Furthermore, community detection, human dynamics, and behavior have also attracted scholars’ attention [244–249]. Finally, Lenz et al. [250] have analyzed intelligent learning and evaluation mechanisms in schools and universities with wearable devices.

Smart Living

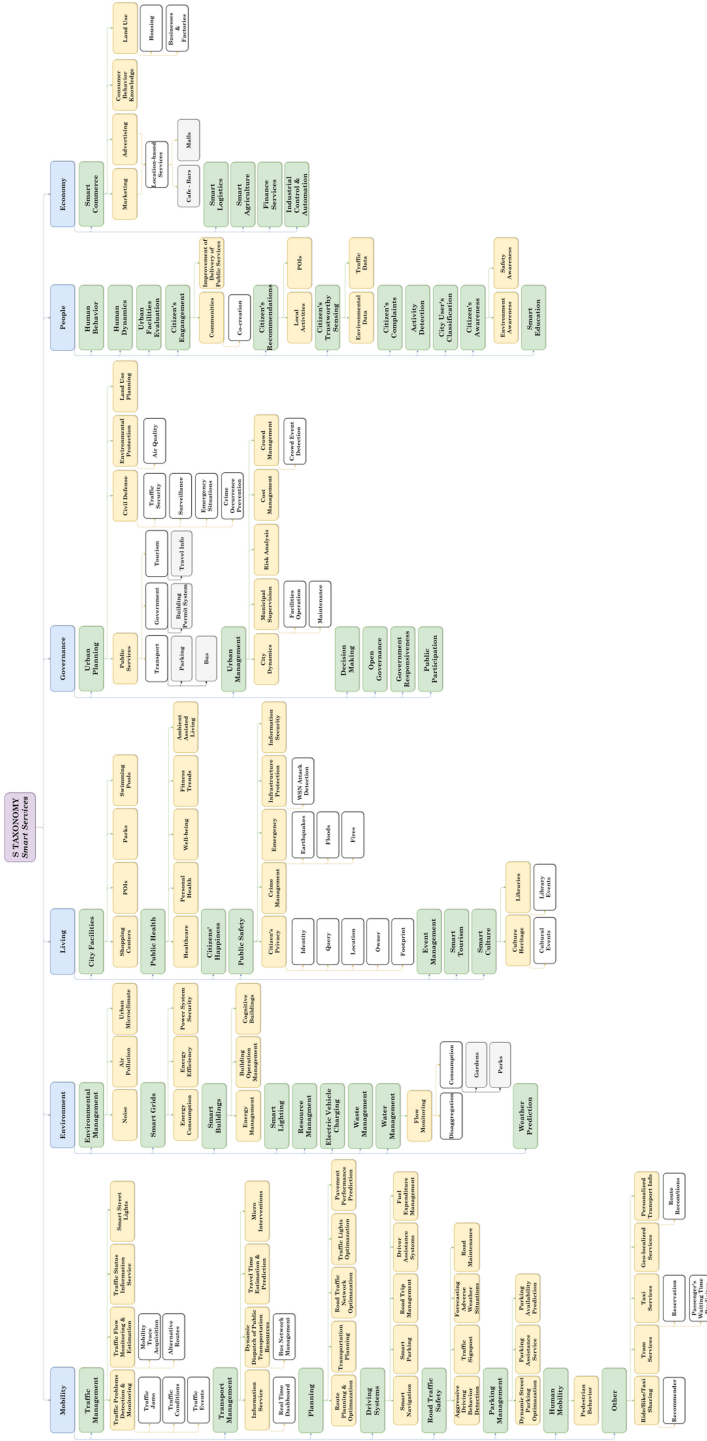
This class of services deal with urban facilities (e.g., parks, swimming pools, shopping centers, universities) [84, 106, 181, 200, 251, 252]; cultural events and activities, and touristic paths that make the city attractive to visitors and tourists [69, 98, 253]; safety and emergency [143, 254, 255]; and health and care [71, 82, 256, 257].

Smart Economy

Smart economy addresses local growth and how it can be achieved based on the digital economy, entrepreneurship, flexibility of labor market, logistics, and so on [258, 259].

Combination of Smart Services

DM and DH can be utilized for smart services that deal with more than one SC dimension. For instance, transportation produces emissions (NO_x, CO₂ PMs, etc.) that harm the environment [260, 261] and affect the local quality of life and a community’s health [262, 263]. On the other hand, public safety deals with smart living and smart governance [197, 265, 266]. Furthermore, citizens’



Schema 3. The “S” Taxonomy outline.

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 [180, 267, 268].

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). The “DMS” taxonomy is scalable and offers the basis for classification of future work, in order to achieve a 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 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 SCs, 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. 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 that 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, journals, 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 the SC era.

Use Case 3: Local Government Agency Adoption

A technical advisor of C city’s mayor and the city council have recently decided to take action to turn their city into a SC. 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

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

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), 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). 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 SC.

6 ONGOING STATE-OF-THE-ART AND TRENDS

Since this systematic review covered literature analysis before the end of 2017, results of published work until 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 are even 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 article’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.

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). With regard to the context of the articles, scholars keep paying 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* [269] that belongs to smart living dimension; *transportation resilience* [270] that addresses smart mobility dimension; *energy usage patterns for load prediction* [271, 272] that deals with smart environment and smart governance dimensions; *indoor space quality* as related with smart buildings and is measured by human behavior [273];

and *crime prediction* via criminal behavioral analysis [274], 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 in the following:

- There’s an increasing *shift from SC smart dimensions to SC smart services*: more specifically, more and more scholars (i.e., [269, 270, 275–277]) 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., [274, 278–283]) and *cyber-physical systems analysis* (e.g., [269, 284]).

7 CONCLUSIONS

This article 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 article 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 article focused on Data Harvesting and Data Mining in SC.

For the purposes of this review, the authors followed the Kitchenham [50] 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 five research questions (RQ1–RQ5), which were relative to the purposes of this article. Results show that an emerging number of articles has been published (Figure 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 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, and 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 a preference to applications that analyze human behavior for several purposes (e.g., environment, mobility, consuming).

Classifying the smart services, which have been developed so far, in the six proposed dimensions of SCs proposed by Giffinger and 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 initiatives, emphasis has been placed on smart mobility which largely facilitates transport and leads to saving time and enhancing city's energy efficiency (e.g., fuels, road maintenance costs), combined with the relative ease of collecting mobility data (e.g., transfer cards, fixed devices on roads). 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]). 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. Along 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). On the other hand, the wide context of methods and techniques for DH and 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 article'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 article'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 those 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), 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.

REFERENCES

- [1] Leonidas G. Anthopoulos. 2017. *Understanding Smart Cities: A Tool for Smart Government or an Industrial Trick?*. Springer International Publishing. DOI: [10.1007/978-3-319-57015-0](https://doi.org/10.1007/978-3-319-57015-0)
- [2] Michael Batty, Kay W. Axhausen, Fosca Giannotti, Alexei Pozdnoukhov, Armando Bazzani, Monica Wachowicz, Georgios Ouzounis, and Yuval Portugali. 2012. Smart cities of the future. *The European Physical Journal Special Topics* 214, 1 (November 2012), 481–518. DOI: <http://dx.doi.org/10.1140/epjst/e2012-01703-3>
- [3] Vito Albino, Umberto Berardi, and Rosa M. Dangelico. 2015. Smart cities: Definitions, dimensions, performance, and initiatives. *Journal of Urban Technology* 22, 1 (February 2015), 3–21. DOI: <http://dx.doi.org/10.1080/10630732.2014.942092>
- [4] Nicos Komminos, Marc Pallot, and Hans Schaffers. 2013. *Journal of Knowledge Economy* 4 (2013), 119. DOI: <https://doi.org/10.1007/s13132-012-0083-x>
- [5] Hafedh Chourabi, Nam Taewoo, Shawn Walker, J. Ramon. Gil-Garcia, Sehl Mellouli, Karine Nahon, Theresa A. Pardo, and Hans J. Scholl. 2012. Understanding smart cities: An integrative framework. In *Proceedings of the 45th Hawaii International Conference on System Science (HICSS'12)*, 2289–2297. DOI: <https://doi.org/10.1109/HICSS.2012.615>
- [6] Annalisa Cocchia. 2014. Smart and digital city: A systematic literature review. *Smart City*, R. P. Dameri and C. Rosenthal-Sabroux (Eds.), Progress in IS, Springer International Publishing Switzerland, 13–43. DOI: http://dx.doi.org/10.1007/978-3-319-06160-3_2
- [7] Leonidas G. Anthopoulos. 2015. Understanding the smart city domain: A literature review. *Transforming City Governments for Successful Smart Cities*, M. P. Rodriguez-Bolivar (Ed.). Public Administration and Information Technology 8, Springer International Publishing Switzerland, 9–21. DOI: http://dx.doi.org/10.1007/978-3-319-03167-5_2
- [8] International Standards Organization (ISO). 2015. Smart community infrastructures—Principles and requirements for performance metrics. Retrieved August 2016 from <https://www.iso.org/obp/ui/#iso:std:iso:ts:37151:ed-1:v1:en>.
- [9] ISO/IEC JTC1 Information Technology. 2015. Smart Cities. Retrieved May 15, 2017 from http://www.iso.org/iso/smart_cities_report-jtc1.pdf.
- [10] Rudolf Giffinger and Haindlmaier Gudrun. 2010. Smart cities ranking: An effective instrument for the positioning of cities?. *ACE* 4, 12 (February 2010), 7–25, URL: <http://hdl.handle.net/2099/8550>
- [11] International Telecommunications Union (ITU). 2014. Anonymization infrastructure and open data in smart sustainable cities. Retrieved December 2017 from <http://www.itu.int/en/ITU-T/focusgroups/ssc/Pages/default.aspx>.
- [12] Rob Kitchin. 2014. The real-time city? Big data and smart urbanism. *GeoJournal* 79, 1 (February 2014), 1–14. DOI: <https://doi.org/10.1007/s10708-013-9516-8>
- [13] Ignasi Vilajosana, Jordi Llosa, Borja Martinez, Marc Domingo-Prieto, Albert Angles, and Xavier Vilajosana. 2013. Bootstrapping smart cities through a self-sustainable model based on big data flows. *IEEE Communications Magazine* 51, 6 (June 2013), 128–134. DOI: <https://doi.org/10.1109/MCOM.2013.6525605>
- [14] Eiman Al Nuaimi, Hind Al Neyadi, Nader Mohamed, and Jameela Al-Jaroodi. 2015. Applications of big data to smart cities. *Journal of Internet Services and Applications* 6, 25. DOI: <https://doi.org/10.1186/s13174-015-0041-5>
- [15] Martin Strohbach, Holger Ziekow, Vangelis Gazis, and Navot Akiva. 2015. Towards a big data analytics framework for IoT and smart city applications. In *Modeling and Processing for Next-Generation Big-Data Technologies*. Modeling and Optimization in Science and Technologies 4. F. Xhafa, L. Barolli, A. Barolli, and P. Papajorgji (Eds.). Springer, Cham. DOI: https://doi.org/10.1007/978-3-319-09177-8_11

- [16] Smart Cities Council. 2016. Examples and case studies. Retrieved June 20, 2017 from <http://smartcitiescouncil.com/smart-cities-information-center/examples-and-case-studies>.
- [17] Vaia Moustaka, Athena Vakali, and Leonidas G. Anthopoulos. 2017. CityDNA: Smart city dimensions' correlations for identifying urban profile. In *Proceedings of the 26th International World Wide Web Conference (WWW'17)*, ACM. DOI: <https://doi.org/10.1145/3041021.3054714>
- [18] Ina Schieferdecker, Nikolay Tcholtchev, and Philipp Lämmel. 2016. Urban data platforms—An overview. In *OpenSym'16 Companion*, ACM. DOI: <http://dx.doi.org/10.1145/2962132.2984894>
- [19] Chetal S. Patil and Kanaksing N. Pawar. 2016. A review on: Protocols and standards in different application areas of IOT. *IJARCCCE* 5, 2 (February 2016), 163–168. DOI: <http://dx.doi.org/10.17148/IJARCCCE.2016.5235.163>
- [20] Chun W. Tsai, Chin F. Lai, Ming C. Chiang, and Laurence T. Yang. 2014. Data mining for internet of things: A survey. *IEEE Communications Surveys & Tutorials* 16, 1 (First Quarter 2014), 77–97. DOI: <http://dx.doi.org/10.1109/SURV.2013.103013.00206>
- [21] Feng Chen, Pan Deng, Jiafu Wan, Daqiang Zhang, Athanasios V. Vasilakos, and Xiaohui Rong. 2015. Data mining for the internet of things: Literature review and challenges. *International Journal of Distributed Sensor Networks* 2015, 14 pages. DOI: <http://dx.doi.org/10.1155/2015/431047>
- [22] Francesco Calabrese, Laura Ferrari, and Vicent D. Blondel. 2015. Urban sensing using mobile phone network data: A survey of research. *ACM Computing Surveys* 47, 2 (January 2015). DOI: <https://doi.org/10.1145/2655691>
- [23] Soufiene Djahel, Ronan Doolan, Gabriel M. Muntean, and John Murphy. 2015. A communications-oriented perspective on traffic management systems for smart cities: Challenges and innovative approaches. *IEEE Communication Surveys & Tutorials* 17, 1 (First Quarter 2015), 125–151. DOI: <http://dx.doi.org/10.1109/COMST.2014.2339817>
- [24] Xiao Wang, Xinhui Zheng, Qingpeng Zhang, Tao Wang, and Dayong Shen. 2016. Crowdsourcing in ITS: The state of the work and the networking. *IEEE Transactions on Intelligent Transportation Systems* 17, 6 (June 2016), 1596–1605. DOI: <http://dx.doi.org/10.1109/TITS.2015.2513086>
- [25] Xinhui Zheng, Wei Chen, Pu Wang, Dayong Shen, Songhang Chen, Xiao Wang, Qingpeng Zhang, and Liuqing Yang. 2016. Big data for social transportation. *IEEE Transactions on Intelligent Transportation Systems* 17, 3 (March 2016), 620–630. DOI: <http://dx.doi.org/10.1109/TITS.2015.2480157>
- [26] Bernard Marr. 2017. 17 'Internet Of Things' Facts Everyone Should Read. Forbes. Retrieved December 2017 from <https://www.forbes.com/sites/bernardmarr/2015/10/27/17-mind-blowing-internet-of-things-facts-everyone-should-read/#7694cbee3505>.
- [27] Dan Rosenbaum. 2017. Smart cities: Who Owns the Data?. *Hewlett Packard Enterprise*. Retrieved December 2017 from <https://www.hpe.com/us/en/insights/articles/smart-cities-who-owns-the-data-1705.html>.
- [28] Andy Bowker. 2017. Making Smart Cities a Reality: How to Handle Big Data. Retrieved December 2017 from <https://www.itproportal.com/features/making-smart-cities-a-reality-how-to-handle-big-data/>.
- [29] International Standards Organization (ISO). 2016. Sustainable development in communities. Retrieved December 2017 from http://www.iso.org/iso/iso_37101_sustainable_development_in_communities.pdf.
- [30] British Standards Institute (BSI). 2016. Mapping smart city standards: Based on a data flow model. Retrieved December 2017 from <http://www.bsigroup.com/en-GB/smart-cities/smart-cities-standards-mapping-research-and-modelling/>.
- [31] Michael Chui, Markus Löffler, and Roger Roberts. 2010. The internet of things. *McKinsey Quarterly* (March 2010). Retrieved June 20, 2017 from <http://www.mckinsey.com/industries/high-tech/our-insights/the-internet-of-things>.
- [32] Enrique Estellés-Arolas and Fernando González—"Ladróna"—de-Guevara. 2012. Towards an integrated crowdsourcing definition. *Journal of Information Science* 38, 2 (2012), 1–14. DOI: <http://dx.doi.org/0.1177/0165551500000000>
- [33] Bin Guo, Zhu Wang, Zhiwen Yu, Yu Wang, Neil Y. Yen, Runhe Huang, and Xingshe Zhou. 2015. Mobile crowd sensing and computing: The review of an emerging human-powered sensing paradigm. *ACM Computing Surveys* 48, 1 (2015), Article 7 (August 2015), 31 pages. DOI: <http://dx.doi.org/10.1145/2794400>
- [34] Javier Miranda, Niko Mäkitalo, Jose Garcia-Alonso, Javier Berrocal, Tommi Mikkonen, Carlos Canal, and Juan M. Murillo. 2015. From the internet of things to the internet of people. *IEEE Internet Computing* 19, 2 (Mar-Apr. 2015), 40–47. DOI: <https://doi.org/10.1109/MIC.2015.24>
- [35] Athena Vakali, Lefteris Angelis, and Maria Giatsoglou. 2013. Sensors talk and humans sense towards a reciprocal collective awareness smart city framework. In *Proceedings of the 2013 IEEE International Communications Workshops (ICC'13)*, IEEE, 189–193. DOI: <http://dx.doi.org/10.1109/ICCW.2013.6649226>
- [36] Gartner IT Glossary. 2017. What is Big Data?. Retrieved June 15, 2017 from <https://research.gartner.com/definition-what-is-big-data?resId=3002918&srcId=1-8163325102>.
- [37] Bernard Marr. 2015. Why Only One of the 5 Vs of Big Data Really Matters. Retrieved June 2017 from <http://www.ibmbigdatahub.com/blog/why-only-one-5-vs-big-data-really-matters>.
- [38] Ellen Broad. 2015. Closed, shared, open data: What's in a name?. Retrieved June 15, 2017 from <https://theodi.org/blog/closed-shared-open-data-whats-in-a-name>.

- [39] Sören Auer, Christian Bizer, Georgi Kobilarov, Jens Lehmann, Richard Cyganiak, and Zachary Ives. 2007. DBpedia: A nucleus for a web of open data. ISWC/ASWC 2007, K. Aberer et al. (Eds.), *Lecture Notes in Computer Science* Vol. 4825, Springer-Verlag, Berlin, 722–735. DOI: http://dx.doi.org/10.1007/978-3-540-76298-0_52
- [40] Snowflakesoftware. 2016. Data harvesting: On-time, accurate and easy delivery of data. *White Article*. Retrieved June 29 2017 from <https://jio3n19dxjh2x0df120u32x1-wpengine.netdna-ssl.com/wp-content/uploads/2012/03/DataHarvesting.pdf>.
- [41] Techopedia. 2017. Definition of Raw Data. Retrieved September 2017 from <https://www.techopedia.com/definition/1230/raw-data>.
- [42] S.-S. Baskar, L. Arockiam, and S. Charles. 2017. A systematic approach on data pre-processing in data mining. 2013. COMPUSOFT. *An International Journal of Advanced Computer Technology* 2, 11 (November 2013).
- [43] Katarina Grolinger, Wilson A. Higashino, Abhinav Tiwari, and Miriam A.-M. Capretz. 2013. Data management in cloud environments: NoSQL and NewSQL data stores. *Journal of Cloud Computing: Advances, Systems and Applications* 2, 22 (2013). DOI: [10.1186/2192-113X-2-22](https://doi.org/10.1186/2192-113X-2-22)
- [44] Ian Robinson, Jim Webber, and Emil Eifrem. 2015. *Graph Databases* (2nd Ed.). O'Reilly.
- [45] Sapna Jain and M. Afshar Alam. 2017. Comparative study of traditional database and cloud computing database. *International Journal of Advanced Research in Computer Science* 8, 2 (March 2017).
- [46] Cristian Chilipirea, Andreea-Cristina, PetreLoredana-Marsilia Groza, CiprianDobre, and Florin Pop. 2017. An integrated architecture for future studies in data processing for smart cities. *Microprocessors and Microsystems* 52 (July 2017), 335–342. DOI: <https://doi.org/10.1016/j.micpro.2017.03.004>
- [47] Hnin-Y. Shwe, Tseng K. Jet, and Peter H.-J. Chong. 2016. An IoT-oriented data storage framework in smart city applications. In *Proceedings of the 2016 International Conference on Information and Communication Technology Convergence (ICTC'16)*, IEEE. DOI: <https://doi.org/10.1109/ICTC.2016.7763446>
- [48] Mehmed Kantardzic. 2011. *Data Mining, Concepts, Models, Methods and Algorithms* (2nd. ed.). Wiley, New York, NY.
- [49] Amir Gandomi and Murtaza Haider. 2015. Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management* 35 (2015), 137–144. DOI: <https://doi.org/10.1016/j.ijinfomgt.2014.10.007>
- [50] Barbara Kitchenham. 2004. *Procedures for Performing Systematic Reviews*. Technical Report TR/SE-0401. Keele University, UK.
- [51] Barbara Kitchenham and Stuart Charters. 2007. *Guidelines for Performing Systematic Literature Reviews in Software Engineering*. Technical Report EBSE-2007-01. Keele University, UK.
- [52] Barbara Kitchenham and Pearl Brereton. 2013. A systematic review of systematic review process research in software engineering. *Journal Information and Software Technology* 55, 12 (December 2013), 2049–2075. DOI: <https://doi.org/10.1016/j.infsof.2013.07.010>
- [53] Georgios Spanos and Lefteris Angelis. 2016. The impact of information security events to the stock market: A systematic literature review. *Computers & Security* 50 (2016), 216–229. DOI: <https://doi.org/10.1016/j.cose.2015.12.006>
- [54] Katie Alice. 2013. Top 11 Trusted (and Free) Search Engines for Scientific and Academic Research. Retrieved 15 July, 2017 from <http://www.emergingedtech.com/2013/12/top-11-trusted-and-free-search-engines-for-scientific-and-academic-research/>.
- [55] Liana Daren. 2017. The 6 BEST Search Engines for Academic Research NOT Named Google. Retrieved July 15, 2017 from <http://www.teachercast.net/2017/06/01/6-best-search-engines-academic-research/>.
- [56] Jan Brophy and David Bawden. 2005. Is Google enough? Comparison of an internet search engine with academic library resources. In *Aslib Proceedings* 57, 6 (2005), 498–512. DOI: <https://doi.org/10.1108/00012530510634235>
- [57] Mark Deakin and Husam Al Waer. 2012. *From Intelligent to Smart Cities*. Routledge, New York, NY.
- [58] Martin Halvey and Mark T. Keane. 2007. An assessment of tag presentation techniques. In *Proceedings of the 16th International Conference on World Wide Web (WWW'07)*. ACM, New York, 1313–1314. DOI: [10.1145/1242572.1242826](https://doi.org/10.1145/1242572.1242826)
- [59] Marti A. Hearst and Daniela Rosner. 2008. Tag clouds: Data analysis tool or social signaller?. In *Proceedings of the 41st Annual Hawaii International Conference on System Sciences (HICSS'08)*. IEEE Computer Society, 160. DOI: [10.1109/HICSS.2008.422](https://doi.org/10.1109/HICSS.2008.422)
- [60] Thomas Liebig, Nico Piatkowski, Christian Bockermann, and Katharina Morik. 2016. Dynamic route planning with real-time traffic predictions. *Information Systems* (January 2016). DOI: <http://dx.doi.org/10.1016/j.is.2016.01.007>
- [61] Luigi Atzori, Davide Carboni, and Antonio Iera. 2012. Smart things in the social loop: Paradigms, technologies, and potentials. *Ad Hoc Networks* 18 (July 2014), 121–132. DOI: <http://dx.doi.org/10.1016/j.adhoc.2013.03.012>
- [62] Sefki Kolozali, Daniel Puschmann, Maria Bermudez-Edoy, and Payam Barnaghi. 2016. On the effect of adaptive and non-adaptive analysis of time-series sensory data. *IEEE Internet of Things Journal*. DOI: <http://dx.doi.org/10.1109/JIOT.2016.2553080>
- [63] Andrew Crooks, Dieter Pfoser, Andrew Jenkins, Arie Croitoru, Anthony Stefanidis, Duncan Smith, Sophia Karagiorgou, Alexandros Efentakis, and George Lamprianidis. 2014. Crowdsourcing urban form and function. *International Journal of Geographical Information Science*. DOI: <http://dx.doi.org/10.1080/13658816.2014.977905>

- [64] Paolo Bellavista, Giuseppe Cardone, and Antonio Corradi. 2013. Convergence of MANET and WSN in IoT urban scenarios. *IEEE Sensors Journal* 13, 10 (October 2013), 3558–3567. DOI : <http://dx.doi.org/10.1109/JSEN.2013.2272099>
- [65] Alessandro Bazzi, Barbara Mavi Masini, Gianni Pasolini, and Oreste Andrisano. 2013. Smart navigation in intelligent transportation systems: Service performance and impact on wireless networks. *International Journal on Advances in Telecommunications* 6, 1 & 2 (2013), 57–70.
- [66] Giuseppe Rizzo, Rosa Meo, Ruggero G. Pensa, Giacomo Falcone, and Raphaël Troncy. 2016. Shaping city neighborhoods leveraging crowd sensor. *Information Systems*, July 2016. DOI : <http://dx.doi.org/10.1016/j.engappai.2012.05.005>
- [67] Nicola Bicocchi and Marco Mamei. 2014. Investigating ride sharing opportunities through mobility data analysis. *Pervasive and Mobile Computing* 14 (October 2014), 83–94. DOI : <http://dx.doi.org/10.1016/j.pmcj.2014.05.010>
- [68] Giuseppe Cardone, Andrea Cirri, Antonio Corradi, and Luca Foschini. 2014. The participat mobile crowd sensing living lab: The testbed for smart cities. *IEEE Communications Magazine* 52, 10 (October 2014), 78–85. DOI : <http://dx.doi.org/10.1109/MCOM.2014.6917406>
- [69] Yunchuan Sun, Houbing Song, Antonio J. Jara, and Rongfang Bie. 2016. Internet of things and big data analytics for smart and connected communities. *IEEE Access* 4 (February 2016), 766–773. DOI : <http://dx.doi.org/10.1109/ACCESS.2016.2529723>
- [70] Feixiong Luo, Guofeng Cao, Kevin Mulligan and Xiang Li. 2016. Explore spatiotemporal and demographic characteristics of human mobility via Twitter: A case study of Chicago. *Applied Geography* 70 (May 2016), 11–25. DOI : <http://dx.doi.org/10.1016/j.apgeog.2016.03.001>
- [71] Wei Yang, Lan Mu, and Ye Shen. 2015. Effect of climate and seasonality on depressed mood among twitter users. *Applied Geography* 63 (September 2015), 184–191. DOI : <http://dx.doi.org/10.1016/j.apgeog.2015.06.017>
- [72] Awais Ahmad, Mazhar Rathore, Anand Paul, and Suengmin Rho. 2016. Defining human behaviors using big data analytics in social internet of things. In *Proceedings of the 30th International Conference on Advanced Information Networking and Applications Workshops (WAINA '16)*, IEEE Computer Society, 1101–1107. DOI : <http://dx.doi.org/10.1109/AINA.2016.104>
- [73] Wei-Ju Huang. 2012. ICT-oriented urban planning strategies: A case study of Taipei City, Taiwan. *Journal of Urban Technology* 19, 3 (2012), 41–61. DOI : <http://dx.doi.org/10.1080/10630732.2011.642570>
- [74] Feng Wang, Liang Hu, Dongdai Zhou, Rui Sun, Jiejun Hu, and Kuo Zhao. 2015. Estimating online vacancies in real-time road traffic monitoring with traffic sensor data stream. *Ad Hoc Networks* 35 (December 2015), 3–13. DOI : <http://dx.doi.org/10.1016/j.adhoc.2015.07.003>
- [75] Wang Tao. 2013. Interdisciplinary urban GIS for smart cities: Advancements and opportunities. *Geo-spatial Information Science* 16, 1 (2013), 25–34. DOI : <http://dx.doi.org/10.1080/10095020.2013.774108>
- [76] Chengming Li, Po Liu, Jie Yin, and Xiaoli Liu. 2016. The concept, key technologies and applications of temporal-spatial information infrastructure. *Geo-spatial Information Science* 19, 2 (2016), 148–156. DOI : <http://dx.doi.org/10.1080/10095020.2016.1179440>
- [77] Jayavardhana Gubbi, Rajkumar Buyya, Slaven Marusic, and Marimuthu Palaniswami. 2013. Internet of things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems* 29, 7 (September 2013), 1645–1660. DOI : <http://dx.doi.org/10.1016/j.future.2013.01.010>
- [78] Jiong Jin, Jayavardhana Gubbi, Slaven Marusic, and Marimuthu Palaniswami. 2014. An Information framework for creating a smart city through internet of things. *IEEE Internet of Things Journal* 1, 2 (April 2014), 112–121. DOI : <http://dx.doi.org/10.1109/JIOT.2013.2296516>
- [79] Mark Bennett and John Lehman. 2003. Building a Taxonomy. HighClassify – NIE Enterprise Search, 2 (June 2003). Retrieved November 2017 from <http://www.ideaeng.com/building-a-taxonomy-0102>.
- [79] Daniel F. Macedo, Sérgio de Oliveira, Fernando A. Teixeira, André L. L. Aquino, and Ricardo Augusto Rabelo. 2012. (CIA)2-ITS: Interconnecting mobile and ubiquitous devices for intelligent transportation systems. In *Proceedings of the 2012 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops '12)*, IEEE, 447–450. DOI : <http://dx.doi.org/10.1109/PerComW.2012.6197531>
- [80] Stamatis Karnouskos, Per Goncalves Da Silva, and Dejan Ilic. 2012. Energy services for the smart grid city. In *Proceedings of the 6th IEEE International Conference on Digital Ecosystems and Technologies (DEST'12)*, IEEE. DOI : <http://dx.doi.org/10.1109/DEST.2012.6227925>
- [81] Chun-Hsiang Lee, David Birch, Chao Wu, Dilshan Silva, Orestis Tsinalis, Yang Li, Shulin Yan, Moustafa Ghanem, and Yike Guo. 2013. Building a generic platform for big sensor data application. In *Proceedings of the 2013 IEEE International Conference on Big Data (Big Data '13)*, IEEE, 94–102. DOI : <http://dx.doi.org/10.1109/BigData.2013.6691559>
- [82] T. Nef, P. Urwyler, M. Büchler, I. Tarnanas, R. Stucki, D. Cazzoli, R. Müri, and U. Mosimann. 2015. Evaluation of three state-of-the-art classifiers for recognition of activities of daily living from smart home ambient data. *Sensors* 15, 5 (2015) 11725–11740. DOI : [10.3390/s150511725](https://doi.org/10.3390/s150511725)
- [83] Maria Fazio, Antonio Celesti, Massimo Villari, and Antonio Puliafito. 2014. The need of a hybrid storage approach for IoT in PaaS cloud federation. In *Proceedings of the 28th International Conference on Advanced Information Networking*

- and Applications Workshops (WAINA'14)*, IEEE Computer Society, 779–784. DOI: <http://dx.doi.org/10.1109/WAINA.2014.162>
- [84] S. Rinaldi, F. Bittenbinder, C. Liu, P. Bellagente, L. C. Tagliabue, and A. L. C. Ciribini. 2016. Bi-directional interactions between users and cognitive buildings by means of smartphone app. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI: [10.1109/ISC2.2016.7580819](https://doi.org/10.1109/ISC2.2016.7580819)
- [85] Dario Bruneo, Salvatore Distefano, Francesco Longo, Giovanni Merlino, Antonio Puliafito, Valeria D'Amico, Marco Sapienza, and Giovanni Torrisi. 2016. Stack4Things as a fog computing platform for smart city applications. In *Proceedings of the 2016 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPs)*, IEEE. DOI: [10.1109/INFCOMW.2016.7562195](https://doi.org/10.1109/INFCOMW.2016.7562195)
- [86] Quyet H. Cao, Imran Khan, Reza Farahbakhsh, Giyyarpuram Madhusudan, Gyu Myoung Lee, and Noel Crespi. 2016. A trust model for data sharing in smart cities. In *Proceedings of the 2016 IEEE International Conference on Communications (ICC'16)*, IEEE. DOI: [10.1109/ICC.2016.7510834](https://doi.org/10.1109/ICC.2016.7510834)
- [87] Lijun Dong and Guoqiang Wang. 2016. Enhanced in-network capabilities of information-centric networks for emerging IoT applications. In *Proceedings of the 2016 IEEE International Conference on Internet of Things (iThings'16) and IEEE Green Computing and Communications (GreenCom'16) and IEEE Cyber, Physical and Social Computing (CPSCom'16) and IEEE Smart Data (SmartData'16)*, IEEE. DOI: [10.1109/iThings-GreenCom-CPSCom-SmartData.2016.128](https://doi.org/10.1109/iThings-GreenCom-CPSCom-SmartData.2016.128)
- [88] Davide Carboni, Alex Gluhak, Julie A. McCann, and Thomas H. Beach. 2016. Contextualising water use in residential settings: A survey of non-ntrusive techniques and approaches. *Sensors* 16, 5 (2016). DOI: [10.3390/s16050738](https://doi.org/10.3390/s16050738)
- [89] Julie Y. Zhu, Yu Zheng, Xiuwen Yi, and Victor O. K. Li. 2016. A Gaussian Bayesian model to identify spatio-temporal causalities for air pollution based on urban big data. In *Proceedings of the 2016 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPs'16)*, IEEE. DOI: [10.1109/INFCOMW.2016.7562036](https://doi.org/10.1109/INFCOMW.2016.7562036)
- [90] Gang Pan, Guande Qi, Wangsheng Zhang, Shijian Li, Zhaohui Wu, and Laurence T. Yang. 2013. Trace analysis and mining for smart cities: Issues, methods, and applications. *IEEE Communications Magazine* 51, 6 (June 2013), 120–126. DOI: <http://dx.doi.org/10.1109/MCOM.2013.6525604>
- [91] Daqing Zhang, Lin Sun, Bin Li, Chao Chen, Gang Pan, Shijian Li, and Zhaohui Wu. 2015. Understanding taxi service strategies from taxi GPS traces. *IEEE Transactions on Intelligent Transportation Systems* 16, 1 (February 2015), 123–135. DOI: <http://dx.doi.org/10.1109/TITS.2014.2328231>
- [92] Yongtao Yu, Jonathan Li, Haiyan Guan, and Cheng Wang. 2015. Automated extraction of urban road facilities using mobile laser scanning data. *IEEE Transactions on Intelligent Transportation Systems* 16, 4 (August 2015), 2167–2181. DOI: <http://dx.doi.org/10.1109/TITS.2015.2399492>
- [93] Ana B. Rodríguez-González, Mark R. Wilby, Juan J. Vinagre-Díaz, and Carmen Sánchez-Ávila. 2014. Modeling and detecting aggressiveness from driving signals. *IEEE Transactions on Intelligent Transportation Systems* 15, 4 (August 2014), 1419–1428. DOI: <http://dx.doi.org/10.1109/TITS.2013.2297057>
- [94] Juan C. García-Palomares, Javier Gutiérrez, and Carmen Mínguez. 2015. Identification of tourist hot spots based on social networks: A comparative analysis of European metropolises using photo-sharing services and GIS. *Applied Geography* 63, (September 2015), 408–417. DOI: <http://dx.doi.org/10.1016/j.apgeog.2015.08.002>
- [95] Alice Marascu, Pascal Pompey, Eric Bouillet, Michael Wurst, Olivier Verscheure, Martin Grund, and Philippe Cudre-Mauroux. 2014. TRISTAN: Real-time analytics on massive time series using sparse dictionary compression. In *Proceedings of the 2014 IEEE International Conference on Big Data (Big Data'14)*, IEEE, 291–300. DOI: <http://dx.doi.org/10.1109/BigData.2014.7004244>
- [96] José F. Arias, Roman Friedrich, Thomas Aichberger, and Andreas Putz. 2015. The Revival of Fixed Infrastructure and Fiber Technology and the Future of Mobile Networks. Retrieved October 14, 2017 from <https://www.strategyand.pwc.com/media/file/The-revival-of-fixed-infrastructure.pdf>.
- [97] Thomas Liebig, Gennady Andrienko, and Natalia Andrienko. 2014. Methods for analysis of spatio-temporal blue-tooth tracking data. *Journal of Urban Technology* 21, 2 (2014), 27–37. DOI: <http://dx.doi.org/10.1080/10630732.2014.888215>
- [98] Neal Lathia, Chris Smith, Jon Froehlich, and Licia Capra. 2013. Individuals among commuters: Building personalised transport information services from fare collection systems. *Pervasive and Mobile Computing* 9, 5 (October 2013), 643–664. DOI: <http://dx.doi.org/10.1016/j.pmcj.2012.10.007>
- [98] Vincenzo Mighali, Giuseppe Del Fiore, Luigi Patrono, Luca Mainetti, Stefano Alletto, Giuseppe Serra, and Rita Cucchiara. 2015. Innovative IoT-aware services for a smart museum. In *Proceedings of the 21st International Conference on World Wide Web (WWW'12 Companion)*, ACM, New York, 527–550. DOI: <https://doi.org/10.1145/2740908.2744711>
- [99] Vanessa Frias-Martinez and Enrique Frias-Martinez. 2014. Spectral clustering for sensing urban land use using Twitter activity. *Engineering Applications of Artificial Intelligence* 35, (October 2014), 237–245. DOI: <http://dx.doi.org/10.1016/j.engappai.2014.06.019>

- [99] Franco Zambonelli. 2015. Engineering self-organizing urban superorganisms. *Engineering Applications of Artificial Intelligence* 41 (May 2015), 325–332. DOI : <http://dx.doi.org/10.1016/j.engappai.2014.10.004>
- [100] Victor Garcia-Font, Carles Garrigues, and Helena Rifà-Pous. 2016. A comparative study of anomaly detection techniques for smart city wireless sensor networks. *Sensors* 16, 6 (2016). DOI : [10.3390/s16060868](https://doi.org/10.3390/s16060868)
- [101] Jun Wu, Kaoru Ota, Mianxiong Dong, and Chunxiao Li. 2016. A hierarchical security framework for defending against sophisticated attacks on wireless sensor networks in smart cities. *IEEE Access* 4 (2016), 416–424. DOI : <https://doi.org/10.1109/ACCESS.2016.2517320>
- [102] John van de Pas, Geert-Jan van Bussel, Mettina Veenstra, and Frans Jorna. 2016. Digital data and the city: An exploration of the building blocks of a smart city architecture. In *book: Digital Information Strategies. From Applications and Content to Libraries and People* (1st ed.), D. P. Baker and W. Evans (Eds.), Chapter 13, Chandos Publishing, 185–198.
- [103] S.-N. Akshay Utama Nambi and R. Venkatesha Prasad. 2016. Toward the development of a techno-social smart grid. *IEEE Communications Magazine* 54, 11 (November 2016), 202–209. DOI : [10.1109/MCOM.2016.1600077CM](https://doi.org/10.1109/MCOM.2016.1600077CM)
- [104] Kazi M. Alam, Mukesh Saini, and Abdulmotaleb El Saddiki. 2015. Toward social internet of vehicles: Concept, architecture and applications. *IEEE Access* 3, (March 2015), 343–357. DOI : <http://dx.doi.org/10.1109/ACCESS.2015.2416657>
- [105] Wei-H. Lee, Kuo-Ping Hwang, and Wen-Bin Wu. 2016. An intersection-to-intersection travel time estimation and route suggestion approach using vehicular ad-hoc network. *Ad Hoc Networks* 43, (June 2016), 71–81. DOI : <https://doi.org/10.1016/j.adhoc.2016.02.001>
- [106] Miaoxi Zhao, Gaofeng Xu, and Yun Li. 2016. Evaluating urban public facilities of Shenzhen by application of open source data. *Geo-Spatial Information Science* 19, 2 (2016), 129–139. DOI : <http://dx.doi.org/10.1080/10095020.2016.1176724>
- [107] Yuanyuan Qiao, Xiaoxing Zhao, Jie Yang, and Jiajia Liu. 2016. Mobile big-data-driven rating framework: Measuring the relationship between human mobility and app usage behavior. *IEEE Network* 30, 3 (May-June 2016), 14–21. DOI : [10.1109/MNET.2016.7474339](https://doi.org/10.1109/MNET.2016.7474339)
- [108] Booma S. Balasubramani, Vivek R. Shivaprabhu, Smitha Krishnamurthy, Isabel F. Cruz, and Tanu Malik. 2016. Ontology-based urban data exploration. In *Proceedings of the 2nd ACM SIGSPATIAL Workshop on Smart Cities and Urban Analytics (UrbanGIS'16)*, Article No. 10, ACM, New York. DOI : <https://doi.org/10.1145/3007540.3007550>
- [109] Ciprian Dobre and Fatos Xhafa. 2014. Intelligent services for big data science. *Future Generation Computer Systems* 37, (July 2014), 267–281. DOI : <http://dx.doi.org/10.1016/j.future.2013.07.014>
- [110] Hugo Hromic, Danh Le Phuoc, Martin Serrano, Aleksandar Antonić, Ivana P. Žarko, Conor Hayes, and Stefan Decker. 2015. Real time analysis of sensor data for the internet of things by means of clustering and event processing. In *Proceedings of the 2015 IEEE International Conference on Communications (ICC'15)*, IEEE, 685–691. DOI : <http://dx.doi.org/10.1109/ICC.2015.7248401>
- [111] Andrew Clarke and Robert Steele. 2011. How personal fitness data can be re-used by smart cities. In *Proceedings of the IEEE 7th International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP'11)*, IEEE, 395–400. DOI : <http://dx.doi.org/10.1109/ISSNIP.2011.6146582>
- [112] Garvita Bajaj, Rachit Agarwal, Georgios Bouloukakakis, Pushpendra Singh, Nikolaos Georgantas, and Valerie Issarny. Towards building real-time, convenient route recommendation system for public transit. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI : [10.1109/ISC2.2016.7580779](https://doi.org/10.1109/ISC2.2016.7580779)
- [113] Julio Borges, Matthias Budde, Oleg Peters, Till Riedel, and Michael Beigl. 2016. Towards two-tier citizen sensing. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI : [1109/ISC2.2016.7580779](https://doi.org/10.1109/ISC2.2016.7580779)
- [114] Zi Wang, Bin Guo, Zhiwen Yu, Wenle Wu, Jiafan Zhang, Zhu Wang, and Huihui Chen. 2016. PublicSense: A crowd sensing platform for public facility management in smart cities. In *Proceedings of the 2016 International IEEE Conferences Ubiquitous Intelligence and Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCom/IoP/SmartWorld)*, IEEE. DOI : [10.1109/UIC-ATC-ScalCom-CBDCom-IoP-SmartWorld.2016.0038](https://doi.org/10.1109/UIC-ATC-ScalCom-CBDCom-IoP-SmartWorld.2016.0038)
- [115] Stefano Chessa, Michele Girolami, Luca Foschini, Raffaele Ianniello, and Antonio Corradi. 2015. Social amplification factor for mobile crowd sensing: The participant experience. In *Proceedings of the 2015 IEEE Symposium on Computers and Communication (ISCC'15)*, IEEE. DOI : <http://dx.doi.org/10.1109/ISCC.2015.7405544>
- [116] Giuseppe Cardone, Antonio Corradi, Luca Fochini, and Raffaele Ianniello. 2016. ParticipAct: A large-scale crowd-sensing platform. *IEEE Transactions on Emerging Topics in Computing* 4, 1 (Jan.-March 2016), 21–32. IEEE. DOI : <https://doi.org/10.1109/TETC.2015.2433835>
- [117] Cataldo Musto, Giovanni Semeraro, Pasquale Lops, and Marco de Gemmis. 2015. CrowdPulse: A framework for real-time semantic analysis of social streams. *Information Systems* 54 (December 2015), 127–146. DOI : <http://dx.doi.org/10.1016/j.is.2015.06.007>
- [118] Jorge E. Camargo, Carlos A. Torres, Oscar H. Martínez, and Francisco A. Gómez. 2016. A big data analytics system to analyze citizens' perception of security. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI : [10.1109/ISC2.2016.7580846](https://doi.org/10.1109/ISC2.2016.7580846)

- [119] Zhihan Lv, Xiaoming Li, Baoyun Zhang, Weixi Wang, Yuanyu Zhu, Jinxing Hu, and Shengzhong Feng. 2016. Managing big city information based on WebVRGIS. *IEEE Access* 4 (January 2016), 407–415. DOI: <http://dx.doi.org/10.1109/ACCESS.2016.2517076>
- [120] Blerim Cici, Emmanouil Alimpertis, Alexander Ihler, and Athina Markopoulou. 2016. Cell-to-cell activity prediction for smart cities. In *Proceedings of the 2016 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS'16)*, IEEE. DOI: [10.1109/INFCOMW.2016.7562207](https://doi.org/10.1109/INFCOMW.2016.7562207)
- [121] Lorenzo Gabrielli, Barbara Furletti, Roberto Trasarti, Fosca Giannotti, and Dino Pedreschi. 2015. City users' classification with mobile phone data. In *Proceedings of the 2015 IEEE International Conference on Big Data (Big Data '15)*, IEEE, 1007–1012. DOI: <http://dx.doi.org/10.1109/BigData.2015.7363852>
- [122] Xin Li, Zhihan Lv, Ihab H. Hijazi, Hongzan Jiao, Li Li, and Kuncheng Li. 2016. Assessment of urban fabric for smart cities. *IEEE Access* 4 (January 2016), 373–382. DOI: <http://dx.doi.org/10.1109/ACCESS.2016.2517072>
- [123] Che M. Ruzinoor, Abdul R. M. Shariff, Biswajeet Pradhan, Mahmud Rodzi-Ahmad, and Mohd S. M. Rahim. 2012. A review on 3D terrain visualization of GIS data: Techniques and software. *Geo-Spatial Information Science* 15, 2 (2012), 105–115. DOI: <http://dx.doi.org/10.1080/10095020.2012.714101>
- [124] Maria L. Marsal-Llacuna and Maria B. López-Ibáñez. 2014. Smart urban planning: Designing urban land use from urban time use. *Journal of Urban Technology* 21, 1 (2014), 39–56. DOI: <http://dx.doi.org/10.1080/10630732.2014.884385>
- [125] Deren Li, Jie Shan, Zhenfeng Shao, Xiran Zhou, and Yuan Yao. 2013. Geomatics for smart cities—Concept, key techniques, and applications. *Geo-spatial Information Science* 16, 1 (2013), 13–24. DOI: <http://dx.doi.org/10.1080/10095020.2013.772803>
- [126] Gloria Re Calegari, Irene Celino, and Diego Peroni. 2016. City data dating: Emerging affinities between diverse urban datasets. *Information Systems* 57 (April 2016), 223–240. DOI: <http://dx.doi.org/10.1016/j.is.2015.08.001>
- [127] Lara Srivastava and Athena Vakali. 2012. Towards a narrative-aware design framework for smart urban environments. *The Future Internet*, F. Alvarez et al. (Eds.), Lecture Notes in Computer Science. Vol. 7281. Springer, 166–177. DOI: http://dx.doi.org/10.1007/978-3-642-30241-1_15
- [128] Athanasios Antoniou, Evangelos Theodoridis, Ioannis Chatzigiannakis, and Georgios Mylonas. 2012. Using future internet infrastructure and smartphones for mobility trace acquisition and social interactions monitoring. *The Future Internet* (2012), 117–129. DOI: http://dx.doi.org/10.1007/978-3-642-30241-1_11
- [129] Emanuele Bellini, Paolo Nesi, Gianni Pantaleo, and Alessandro Venturi. 2016. Functional resonance analysis method based decision support tool for urban transport system resilience management. In *Proceedings of the 2016 IEEE International on Smart Cities Conference (ISC2'16)*, IEEE. DOI: <https://doi.org/10.1109/ISC2.2016.7580833>
- [130] Henrika Pihlajaniemi, Eveliina Juntunen, Anna Luusua, Mirva Tarkka-Salin, and Johan Juntunen. 2016. SenCity—Piloting intelligent lighting and user-oriented services in complex smart city environments. In *Proceedings of eCAADe 2016 Conference*.
- [131] Hadi Bannazadeh, Ali Tizghadam, and Alberto Leon-Garcia. 2016. Smart city platforms on multitier software-defined infrastructure cloud computing. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI: [10.1109/ISC2.2016.7580770](https://doi.org/10.1109/ISC2.2016.7580770)
- [132] Nguyen B. Truong, Quyet H. Cao, Tai-Won Um, and Gyu Myoung Lee. 2016. Leverage a trust service platform for data usage control in smart city. In *Proceedings of the 2016 IEEE Global Communications Conference (GLOBECOM'16)*, IEEE. DOI: [10.1109/GLOCOM.2016.7841951](https://doi.org/10.1109/GLOCOM.2016.7841951)
- [132] Qihui Wu, Guoru Ding, Yuhua Xu, Shuo Feng, Zhiyong Du, Jinlong Wang, and Keping Long. 2014. Cognitive internet of things: A new paradigm beyond connection. *IEEE Internet of Things Journal* 1, 2 (April 2014), 129–143. DOI: <http://dx.doi.org/10.1109/JIOT.2014.2311513>
- [134] Jaime de Miguel-Rodríguez, Juan Galán-Páez, Gonzalo A. Aranda-Corral, and Joaquín Borrego-Díaz. 2016. Urban knowledge extraction, representation and reasoning as a bridge from data city towards smart cities. In *Proceedings of the 2016 International IEEE Conferences Ubiquitous Intelligence and Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCOM/IoP/SmartWorld)*, IEEE. DOI: [10.1109/UIC-ATC-ScalCom-CBDCOM-IoP-SmartWorld.2016.0152](https://doi.org/10.1109/UIC-ATC-ScalCom-CBDCOM-IoP-SmartWorld.2016.0152)
- [135] Athena Vakali, Leonidas Anthopoulos, and Srdjan Krco. 2014. Smart cities data streams integration: Experimenting with internet of things and social data flows. In *Proceedings of the 4th International Conference on Web Intelligence, Mining and Semantics (WIMS'14)*, ACM, New York. DOI: <https://doi.org/10.1145/2611040.2611094>
- [136] Ningyu Zhang, Huajun Chen, Xi Chen, and Jiaoyan Chen. 2016. Semantic framework of internet of things for smart cities: Case studies. *Sensors* 16, 9 (2016). DOI: [10.3390/s16091501](https://doi.org/10.3390/s16091501)
- [137] Antonio Attanasio, Tania Cerquitelli, and Silvia Chiusano. 2016. Supporting the analysis of urban data through NoSQL technologies. In *Proceedings of the 7th International Conference on Information, Intelligence, Systems & Applications (IISA'16)*, IEEE. DOI: [10.1109/IISA.2016.7785334](https://doi.org/10.1109/IISA.2016.7785334)

- [138] Christos Anagnostopoulos. 2016. Intelligent contextual information collection in internet of things. *Intelligent Journal of Wireless Information Networks* 23, 1 (March 2016), 28–39. DOI : <http://dx.doi.org/10.1007/s10776-015-0293-9>
- [139] Antonio Scarfo. 2014. Internet of things, the smart x enabler. In *Proceedings of the 2014 International Conference on Intelligent Networking and Collaborative Systems (INCoS'14)*. IEEE Computer Society, 569–574. DOI : <http://dx.doi.org/10.1109/INCoS.2014.98>
- [140] Charith Perera, Arkady Zaslavsky, Chi H. Liu, Michael Compton, Peter Christen, and Dimitrios Georgakopoulos. 2014. Sensor search techniques for sensing as a service architecture for the internet of things. *IEEE Sensors Journal* 14, 2 (February 2014), 406–420. DOI : <http://dx.doi.org/10.1109/JSEN.2013.2282292>
- [141] Zhihan Lv, Tengfei Yin, Xiaolei Zhang, Houbing Song, and Ge Chen. 2016. Virtual reality smart city based on WebVRGIS. *IEEE Internet of Things Journal* (March 2016). DOI : <http://dx.doi.org/10.1109/JIOT.2016.2546307>
- [142] Masoomeh Zamani, Masud Moshtaghi, and Christopher Leckie. 2016. Efficient query processing on road traffic network. In *Proceedings of the 2016 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops'16)*, IEEE. DOI : <http://dx.doi.org/10.1109/PERCOMW.2016.7457090>
- [143] Antoni Martínez-Ballesté, Pablo A. Pérez-Martínez, and Agusti Solanas. 2013. The pursuit of citizens' privacy: A privacy-aware smart city is possible. *IEEE Communications Magazine* 51, 6 (June 2013), 136–141. DOI : <http://dx.doi.org/10.1109/MCOM.2013.6525606>
- [144] Xiaoguang Niu, Ying Zhu, Qingqing Cao, Xining Zhang, Wei Xie and Kun Zheng. 2015. An online-traffic-prediction based route finding mechanism for smart city. *International Journal of Distributed Sensor Networks* 2015, Article 970256, 16 pages. <http://dx.doi.org/10.1155/2015/970256>
- [145] Zipei Fan, Xuan Song, Ryosuke Shibasaki, and Ryutaro Adachi. 2015. CityMomentum: An online approach for crowd behavior prediction at a citywide level. In *Adjunct Proceedings of the 2015 ACM 4th International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp'15)*, ACM, New York, 559–569. DOI : <https://doi.org/10.1145/2750858.2804277>
- [146] Alberto Rubio, Angel Sanchez, and Enrique Frias-Martinez. 2013. Adaptive non-parametric identification of dense areas using cell phone records for urban analysis. *Engineering Applications of Artificial Intelligence* 26, 1 (January 2013), 551–563. DOI : <http://dx.doi.org/10.1016/j.engappai.2012.05.005>
- [147] Sahn Jiang, Joseph Ferreira, and Marta C. Gonzalez. 2012. Discovering urban spatial-temporal structure from human activity patterns. In *Proceedings of the ACM SIGKDD International Workshop on Urban Computing (UrbComp'12)*, ACM, New York, 95–102. DOI : <https://doi.org/10.1145/2346496.2346512>
- [148] Eleonora D'Andrea, Pietro Ducange, Beatrice Lazzarini, and Francesco Marcelloni. 2015. Real-time detection of traffic from Twitter stream analysis. *IEEE Transactions on Intelligent Transportation Systems* 16, 4 (August 2015), 2269–2283. DOI : <http://dx.doi.org/10.1109/TITS.2015.2404431>
- [149] Verónica Gutiérrez, Evangelos Theodoridis, Georgios Mylonas, Fengrui Shi, Usman Adeel, Luis Diez, Dimitrios Amaxilatis, Johnny Choque, Guillem Camprodom, Julie McCann, and Luis Muñoz. 2016. Co-creating the cities of the future. *Sensors* 16, 11 (2016). DOI : [10.3390/s16111971](https://doi.org/10.3390/s16111971)
- [150] Ármín Petkovics and Károly Farkas. 2014. Efficient event detection in public transport tracking. In *Proceedings of the 2014 International Conference on Telecommunications and Multimedia (TEMU'14)*, IEEE, 74–79. DOI : <http://dx.doi.org/10.1109/TEMU.2014.6917739>
- [151] Thiago Lacerda and Stenio Fernandes. 2016. Scalable real-time flock detection. In *Proceedings of the 2016 IEEE Global Communications Conference (GLOBECOM'16)*, IEEE. DOI : [10.1109/GLOCOM.2016.7842241](https://doi.org/10.1109/GLOCOM.2016.7842241)
- [152] Manuel García and Javier Morales. 2015. GeoSmart cities: Event-driven geoprocessing as enabler of smart cities. In *Proceedings of the 2015 IEEE First International Smart Cities Conference (ISC2'15)*, IEEE. DOI : <http://dx.doi.org/10.1109/ISC2.2015.7366207>
- [153] Paolo Bellavista, Giuseppe Cardone, Antonio Corradi, and Luca Foschini. 2012. The future internet convergence of IMS and ubiquitous smart environments: An IMS-based solution for energy efficiency. *Journal of Network and Computer Applications* 35, 4 (July 2012), 1203–1209. DOI : <http://dx.doi.org/10.1016/j.jnca.2011.05.003>
- [154] Giuseppe Rizzo, Oscar Corcho, Raphaël Troncy, Julien Plu, Juan C. Ballesteros Hermida, and Ahmad Assaf. 2015. The 3city knowledge base for Expo Milano 2015—Enabling visitors to explore the city. In *Proceedings of the 8th International Conference on Knowledge Capture (K-CAP'15)*. ACM, New York, Article No. 18. DOI : <https://doi.org/10.1145/2815833.2816944>
- [155] Nicola Ianaue, Duccio Schiavon, and Enrico Capobianco. 2015. Smart cities, big data, and communities: Reasoning from the viewpoint of attractors. *IEEE Access* 4 (November 2015), 41–47. DOI : <http://dx.doi.org/10.1109/ACCESS.2015.2500733>
- [156] Andras Garzo, Andras A. Benczur, Csaba Istvan Sidlo, Daniel Tahara, and Erik Francis Wyatt. 2013. Real-time streaming mobility analytics. In *Proceedings of the 2013 IEEE International Conference on Big Data (Big Data'13)*, IEEE, 697–702. DOI : <http://dx.doi.org/10.1109/BigData.2013.6691639>

- [157] Christine Jardak, Petri Mähönen, and Janne Riihijärvi. 2014. Spatial big data and wireless networks: Experiences, applications, and research challenges. *IEEE Network* 28, 4 (July-August), 26–31. DOI: [10.1109/MNET.2014.6863128](https://doi.org/10.1109/MNET.2014.6863128)
- [158] Francisco Rebelo, Carlos Soares, Rosaldo J. F. Rossetti, Luis Camacho Caballero, José Luis Calderón Choy, and Reynaldo Baquerizo Micheline. 2015. TwitterJam: Identification of mobility patterns in urban centers based on tweets. In *Proceedings of the 2015 IEEE First International Smart Cities Conference (ISC2'15)*, IEEE. DOI: <http://dx.doi.org/10.1109/ISC2.2015.7366156>
- [159] Thierry Dermann, Raphaël Frank, Sébastien Faye, German Castignani, and Thomas Engel. 2016. Towards privacy-neutral travel time estimation from mobile phone signalling data. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI: [10.1109/ISC2.2016.7580735](https://doi.org/10.1109/ISC2.2016.7580735)
- [160] Gavin Kemp, Pedropablo López Amaya, Catarina Ferreira da Silva, Genoveva Vargas-Solar, Parisa Ghodous, and Christine Collet. 2016. Big data collections and services for building intelligent transport applications. *International Journal of Electronic Business Management, Electronic Business Management Society* 14 (2016).
- [161] Oleksiy Mazhelis, Antti Hämäläinen, Tomi Asp, and Pasi Tyrväinen. 2016. Towards enabling privacy preserving smart city apps. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI: [10.1109/ISC2.2016.7580755](https://doi.org/10.1109/ISC2.2016.7580755)
- [162] Christian Fabbriatore, Harold Boley, and Achim P. Karduck. 2012. Machine learning for resource management in smart environments. In *Proceedings of the 6th IEEE International Conference on Digital Ecosystems and Technologies (DEST'12)*, IEEE. DOI: <http://dx.doi.org/10.1109/DEST.2012.6227910>
- [163] Pierfrancesco Bellini, Ivan Bruno, Paolo Nesi, and Nadia Rauch. 2015. Graph data bases methodology and tool supporting index/store versioning. *Journal of Visual Languages and Computing* 31, Part B (December 2015), 222–229. DOI: <http://dx.doi.org/10.1016/j.jvlc.2015.10.018>
- [164] Carlos Oberdan Rolim, Anubis G. Rossetto, Valderi R. Q. Leithardt, Guilherme A. Borgesa, Cláudio F. R. Geyera, Tatiana F. M. dos Santos, and Adriano M. Souza. 2016. Mobile big-data-driven rating framework: Measuring the relationship between human mobility and app usage behavior. *IEEE Network* 30, 3 (May-June 2016), 14–21. DOI: [10.1109/MNET.2016.7474339](https://doi.org/10.1109/MNET.2016.7474339)
- [168] Weisi Guo, Neha Gupta, Ganna Pogrebna, and Stephen Jarvis. 2016. Understanding happiness in cities using Twitter: Jobs, children, and transport. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI: [10.1109/ISC2.2016.7580790](https://doi.org/10.1109/ISC2.2016.7580790)
- [169] Fang-Jing Wu and Hock Beng Lim. 2014. Urban mobility sense: A user-centric participatory sensing system for transportation activity surveys. *IEEE Sensors Journal* 14, 12 (December 2014), 4165–4174. DOI: <http://dx.doi.org/10.1109/JSEN.2014.2359876>
- [170] Nuria Pazos, M. Muller, M. Favre-Bulle, K. Brandt-Dit-Grieurin, O. Husser, M. Aeberli, and Nabil Ouerhani. 2016. Dynamic street-parking optimisation. In *Proceedings of the 30th International Conference on Advanced Information Networking and Applications Workshops (WAINA'16)*, IEEE, 1020–1026. DOI: <http://dx.doi.org/10.1109/AINA.2016.171>
- [171] Sudha Ram, Fan Dong, Faize Currim, Yun Wang, Ezequiel Dantas, and Luiz Alberto Sabóia. 2016. SMARTBIKE: Policy making and decision support for bike share systems. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI: [10.1109/ISC2.2016.7580838](https://doi.org/10.1109/ISC2.2016.7580838)
- [172] Bo-Wei Chen and Wen Ji. 2016. Intelligent marketing in smart cities: Crowdsourced data for geo-conquesting. *IT Professional* 18, 4 (July-Aug. 2016), 26–33. DOI: [10.1109/MITP.2016.64](https://doi.org/10.1109/MITP.2016.64)
- [173] Ruben Mayer, Boris Koldehofe, and Kurt Rothermel. 2015. Predictable low-latency event detection with parallel complex event processing. *IEEE Internet of Things Journal* 2, 4 (August 2015), 274–286. DOI: <http://dx.doi.org/10.1109/JIOT.2015.2397316>
- [174] Shuo Wang, Richard Sinnott, and Surya Nepal. 2016. Privacy-protected social media user trajectories calibration. In *Proceedings of the 2016 IEEE 12th International Conference on e-Science (e-Science'16)*, IEEE. DOI: <https://doi.org/10.1109/eScience.2016.7870912>
- [175] Yan Lyu. 2016. T2CBS: Mining taxi trajectories for customized bus systems. In *Proceedings of the 2016 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS'16)*, IEEE. DOI: [10.1109/INFCOMW.2016.7562117](https://doi.org/10.1109/INFCOMW.2016.7562117)
- [176] Sefki Kolozali, Maria Bermudez-Edo, Daniel Puschmann, Frieder Ganz, and Payam Barnaghi. 2014. A knowledge-based approach for real-time IoT data stream annotation and processing. In *Proceedings of the 2014 IEEE International Conference on Internet of Things (iThings'14), Green Computing and Communications (GreenCom'14), and Cyber-Physical-Social Computing (CPSCom'14)*, 215–222. IEEE. DOI: <https://doi.org/10.1109/iThings.2014.39>
- [177] Zolzaya Dashdorj and Stanislav Sobolevsky. 2015. Impact of the spatial context on human communication activity. In *Adjunct Proceedings of the 2015 ACM 4th International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers (UbiComp/ISWC'15)*, ACM, New York, 1615–1622. DOI: <https://doi.org/10.1145/2800835.2801625>
- [178] Jiang Zhong, Weili Guo, and Zhenhua Wang. 2016. Study on network failure prediction based on alarm logs. In *Proceedings of the 3rd MEC International Conference on Big Data and Smart City (ICBDSC'16)*, IEEE. DOI: [10.1109/ICBDSC.2016.7460337](https://doi.org/10.1109/ICBDSC.2016.7460337)

- [179] Madhur Behl and Rahul Mangharam. 2016. Interactive analytics for smart cities infrastructures. In *1st International Workshop on Science of Smart City Operations and Platforms Engineering (SCOPE) in partnership with Global City Teams Challenge (GCTC) (SCOPE-GCTC)*, IEEE. DOI: [10.1109/SCOPE.2016.7515055](https://doi.org/10.1109/SCOPE.2016.7515055)
- [180] Xu Du, Onyeka Emebo, Aparna Varde, Niket Tandon, Sreyasi Nag Chowdhury, and Gerhard Weikum. 2016. Air quality assessment from social media and structured data. Pollutants and health impacts in urban planning. In *Proceedings of the 32nd IEEE International Conference on Data Engineering Workshops (ICDEW'16)*, IEEE, 54–59. DOI: <http://dx.doi.org/10.1109/ICDEW.2016.7495616>
- [181] Giuseppe Cardone, Andrea Cirri, Antonio Corradi, Luca Foschini, and Rebecca Montanari. 2014. Activity recognition for smart city scenarios: Google play services vs. MoST facilities. In *Proceedings of the 2014 IEEE Symposium on Computers and Communication (ISCC'14)*, IEEE. DOI: <http://dx.doi.org/10.1109/ISCC.2014.6912458>
- [182] Ivan Nagy, Evgenia Suzdaleva, Pavla Pecherkova, and Krzysztof Urbaniec. 2015. Mixture-based cluster detection in driving-related data. In *Proceedings of the 2015 Smart Cities Symposium Prague (SCSP'15)*, IEEE. DOI: <http://dx.doi.org/10.1109/SCSP.2015.7181548>
- [183] Theodora S. Brisimi, Christos G. Cassandras, Chris Osgood, Ioannis Ch. Paschalidis, and Yue Zhang. 2016. Sensing and classifying roadway obstacles in smart cities: The street bump system. *IEEE Access* 4 (April 2016), 1301–1312. DOI: <http://dx.doi.org/10.1109/ACCESS.2016.2529562>
- [184] Masahiro Miyaji. 2015. Data mining for safety transportation by means of using internet survey. In *Proceedings of the 31st IEEE International Conference on Data Engineering Workshops (ICDEW'15)*, IEEE, 119–123. DOI: <http://dx.doi.org/10.1109/ICDEW.2015.7129561>
- [185] Lixia Bao, Kai Yang, YiBo Wang, and Junfeng Zhao. 2016. A novel pavement performance prediction framework in smart city based on tensor decomposition. In *Proceedings of the 2016 International IEEE Conferences Ubiquitous Intelligence and Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCCom/IoP/SmartWorld)*, IEEE. DOI: [10.1109/UIC-ATC-ScalCom-CBDCCom-IoP-SmartWorld.2016.0171](https://doi.org/10.1109/UIC-ATC-ScalCom-CBDCCom-IoP-SmartWorld.2016.0171)
- [186] Lorenzo Valerio, Andrea Passarella and Marco Conti. 2016. Hypothesis transfer learning for efficient data computing in smart cities environments. In *Proceedings of the 2016 IEEE International Conference on Smart Computing (SMARTCOMP'16)*, IEEE. DOI: [10.1109/SMARTCOMP.2016.7501696](https://doi.org/10.1109/SMARTCOMP.2016.7501696)
- [187] Victor García-Font, Carles Garrigues, and Helena Rifa—Pous. 2015. An architecture for the analysis and detection of anomalies in smart city WSNs. In *Proceedings of the 2015 IEEE First International Smart Cities Conference (ISC2'15)*, IEEE. DOI: <http://dx.doi.org/10.1109/ISC2.2015.7366188>
- [188] Christian Kaiser and Alexei Pozdnoukhov. 2013. Enabling real-time city sensing with kernel stream oracles and MapReduce. *Pervasive and Mobile Computing* 9, 5 (October 2013), 708–721. DOI: <http://dx.doi.org/10.1016/j.pmcj.2012.11.003>
- [189] Arthur Souza, Mickael Figueredo, Nélio Cacho, Daniel Araújo, Jazon Coelho, and Carlos A. Prolo. 2016. Social smart city: A platform to analyze social streams in smart city initiatives. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI: [10.1109/ISC2.2016.7580848](https://doi.org/10.1109/ISC2.2016.7580848)
- [191] Pierfrancesco Bellini, Paolo Nesi, and Gianni Pantaleo. 2015. Benchmarking RDF stores for smart city services. In *Proceedings of the 2015 IEEE International Conference on Smart City/SocialCom/SustainCom (SmartCity'15)*. IEEE Computer Society, 46–49. DOI: <http://dx.doi.org/10.1109/SmartCity.2015.45>
- [192] Jesús Rodríguez-Molina, José-Fernán Martínez, Pedro Castillejo, and Rubén de Diego. 2013. SMArc: A proposal for a smart, semantic middleware architecture focused on smart city energy management. *Hindawi Publishing Corporation International Journal of Distributed Sensor Network* (2013), Article 560418, 17 pages. DOI: <http://dx.doi.org/10.1155/2013/560418>
- [193] Dario Bonino, Federico Rizzo, and Claudio Pastrino. 2016. Block-based realtime big-data processing for smart cities. In *Proceedings of the 2016 IEEE International on Smart Cities Conference (ISC2'16)*, IEEE. DOI: <https://doi.org/10.1109/ISC2.2016.7580768>
- [194] Chaofeng Zhang, Mianxiong Dong, Kaoru Ota, and Minyi Guo. 2016. A social-network-optimized taxi-sharing service. *IT Professional* 18, 4 (July-Aug. 2016), 34–40. DOI: [10.1109/MITP.2016.71](https://doi.org/10.1109/MITP.2016.71)
- [195] Luca Cagliero, Tania Cerquitelli, Silvia Chiusano, Paolo Garza, Giuseppe Ricupero, and Xin Xiao. 2016. Modeling correlations among air pollution-related data through generalized association rules. In *Proceedings of the 2016 IEEE International Conference on Smart Computing (SMARTCOMP'16)*, IEEE. DOI: [10.1109/SMARTCOMP.2016.7501707](https://doi.org/10.1109/SMARTCOMP.2016.7501707)
- [196] Stefano Chessa, Antonio Corradi, and Luca Foschini. 2016. Empowering mobile crowdsensing through social and ad hoc networking. *IEEE Communications Magazine* 54, 7 (July 2016), 108–114. IEEE. DOI: <https://doi.org/10.1109/MCOM.2016.7509387>
- [197] Debopriya Ghosh, Soon Ae Chun, Basit Shafiq, and Nabil R. Adam. 2016. Big data-based smart city platform: Real-time crime analysis. In *Proceedings of the 17th Annual International Conference on Digital Government Research (dg.o'16)*, ACM, New York, 58–66. DOI: <https://doi.org/10.1145/2912160.2912205>

- [198] Ivana P. Žarko, Kresimir Pripuzić, Martin Serrano, and Manfred Hauswirth. 2014. IoT data management methods and optimisation algorithms for mobile publish/subscribe services in cloud environments. In *Proceedings of the 2014 European Conference on Networks and Communications (EuCNC'14)*, IEEE. DOI : <http://dx.doi.org/10.1109/EuCNC.2014.6882657>
- [199] David N. Crowley, Edward Curry, and John G. Breslin. 2013. Closing the loop—From citizen sensing to citizen actuation. In *Proceedings of the 7th IEEE International Conference on Digital Ecosystems and Technologies (DEST'13)*, IEEE. DOI : <http://dx.doi.org/10.1109/DEST.2013.6611338>
- [200] Alberto Del Bimbo, Andrea Ferracani, Daniele Pezzatini, Federico D'Amato, and Martina Sereni. 2014. LiveCities: Revealing the pulse of cities by location-based social networks venues and users analysis. In *Proceedings of the 21st International Conference on World Wide Web (WWW'12 Companion)*, ACM, New York, 163–166. DOI : <https://doi.org/10.1145/2567948.2577035>
- [201] Magdalini Eirinaki, Subhankar Dhar, and Shishir Mathur. 2016. A cloud-based framework for smart permit system for buildings. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI : [10.1109/ISC2.2016.7580821](https://doi.org/10.1109/ISC2.2016.7580821)
- [202] Mohamed ben Kalifa, Rebeca P. Diaz Redondo, and Ana F. Vilas. 2015. Why are these people there? An analysis based on Twitter. In *Proceedings of the 6th International Conference on Information, Intelligence, Systems & Applications (IISA'15)*, 1–6, Corfu, IEEE. DOI : <https://doi.org/10.1109/IISA.2015.7388024>
- [203] Spyridon Vassilaras and Gregory S. Yovanof. 2010. Wireless innovations as enablers for complex and dynamic artificial systems. *Wireless Personal Communications* 53 (2010), 365–393. DOI : <http://dx.doi.org/10.1007/s11277-010-9952-4>
- [204] Julien Nigon, Estèle Glize, David Dupas, Fabrice Crasnier, and Jérémy Boes. 2016. Use cases of pervasive artificial intelligence for smart cities challenges. In *Proceedings of the 2016 International IEEE Conferences Ubiquitous Intelligence and Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCom/IoP/SmartWorld)*, IEEE. DOI : [10.1109/UIC-ATC-ScalCom-CBDCom-IoP-SmartWorld.2016.0159](https://doi.org/10.1109/UIC-ATC-ScalCom-CBDCom-IoP-SmartWorld.2016.0159)
- [205] Paolo Nesi, Gianni Pantaleo, and Marco Tenti. 2016. Geographical localization of web domains and organization addresses recognition by employing natural language processing, pattern matching and clustering. *Engineering Applications of Artificial Intelligence* 51 (May 2016), 202–211. DOI : <http://dx.doi.org/10.1016/j.engappai.2016.01.011>
- [206] Gayathri T. Singh and Fadi M. Al-Turjman. 2016. Learning data delivery paths in QoI-aware information-centric sensor networks. *IEEE Internet of Things Journal* 3, 4 (August 2016), 572–580. DOI : <http://dx.doi.org/10.1109/JIOT.2015.2504487>
- [207] Victoria Moreno-Cano, Fernando Terroso-Saenz, and Antonio F. Skarmeta-Gomez. 2016. Big data for IoT services in smart cities. In *Proceedings of the IEEE 2nd World Forum on Internet of Things (WF-IoT'15)*, IEEE. DOI : <http://dx.doi.org/10.1109/WF-IoT.2015.7389091>
- [208] Eleonora D'Andrea, David Di Lorenzo, Beatrice Lazzarini, Francesco Marcelloni, and Fabio Schoen. 2016. Path clustering based on a novel dissimilarity function for ride-sharing recommenders. In *Proceedings of the 2016 IEEE International Conference on Smart Computing (SMARTCOMP'16)*, IEEE. DOI : [10.1109/SMARTCOMP.2016.7501712](https://doi.org/10.1109/SMARTCOMP.2016.7501712)
- [209] Yanxu Zheng, Sutharshan Rajasegarar, and Christopher Leckie. 2015. Parking availability prediction for sensor-enabled car parks in smart cities. In *Proceedings of the IEEE 10th International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP'15)*, IEEE. DOI : <http://dx.doi.org/10.1109/ISSNIP.2015.7106902>
- [210] Fei-Yue Wang, Charles Hergert, and Daniel Zeng. 2005. Developing and improving transportation systems: The structure and operation of IEEE Intelligent Transportation Systems Society (Guest Editorial). *IEEE Transactions on Intelligent Transportation Systems* 6, 3 (September 2005), 261–264. DOI : <https://doi.org/10.1109/TITS.2005.856949>
- [211] George Dimitrakopoulos and Panagiotis Demestichas. 2010. Intelligent transportation systems. *IEEE Vehicular Technology Magazine* 5, 1 (March 2010), 77–84. DOI : [10.1109/MVT.2009.935537](https://doi.org/10.1109/MVT.2009.935537)
- [212] Xin Cheng, Xiangmo Zhao, Zhigang Xu, Jingmei Zhou, and Nan Yang. 2015. Prediction of the shortest travel time based on intersection delay. In *Proceedings of the 2015 IEEE First International Smart Cities Conference (ISC2'15)*, IEEE. DOI : <http://dx.doi.org/10.1109/ISC2.2015.7366167>
- [213] Vicente R. Tomás, Marta Pla-Castells, Juan José Martínez, and Javier Martínez. 2016. Forecasting adverse weather situations in the road network. *IEEE Transactions on Intelligent Transportation Systems* 17, 8 (August 2016), 2334–2343. DOI : <http://dx.doi.org/10.1109/TITS.2016.2519103>
- [214] Adil A. Sheikh, Ahmed Lbath, Ehsan U. Warriach, Shahbaz A. Awan, Sheikh N. Saeed, and Emad Felemban. 2016. A software platform for smart data-driven intelligent transport applications. In *Proceedings of the 2016 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops'16)*, IEEE. DOI : <http://dx.doi.org/10.1109/PERCOMW.2016.7457091>
- [215] Karoly Farkas, Gabor Feher, Andras Benczur, and Csaba Sidlo. 2015. Crowdsensing based public transport information service in smart cities. *IEEE Communications Magazine* 53, 8 (August 2015), 158–165. DOI : <http://dx.doi.org/10.1109/MCOM.2015.7180523>

- [216] Paolo Nesi, Claudio Badii, Pierfranco Bellini, Daniele Cenni, Giacomo Martelli and Michela Paolucci. 2016. Km4City smart city API: An integrated support for mobility services. In *Proceedings of the 2016 IEEE International Conference on Smart Computing (SMARTCOMP'16)*, IEEE. DOI : <https://doi.org/10.1109/SMARTCOMP.2016.7501702>
- [217] Yanxu Zheng, Sutharshan Rajasegarar, Christopher Leckie, and Marimuthu Palaniswami. 2014. Smart car parking: Temporal clustering and anomaly detection in urban car parking. In *Proceedings of the IEEE 9th International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP'14)*, IEEE. DOI : <http://dx.doi.org/10.1109/ISSNIP.2014.6827618>
- [218] Ardi Imawan, Fitri Indra Indikawati, Joonho Kwon, and Praveen Rao. 2016. Querying and extracting timeline information from road traffic sensor data. *Sensors* 16, 9 (2016). DOI : [10.3390/s16091339](https://doi.org/10.3390/s16091339)
- [219] Yun Wang, Sudha Ram, Faiz Currim, Ezequiel Dantas, and Luiz Alberto Sabóia. 2016. A big data approach for smart transportation management on bus network. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI : [10.1109/ISC2.2016.7580839](https://doi.org/10.1109/ISC2.2016.7580839)
- [220] Jakub Vorel, Daniel Franke, and Martin Silha. 2015. Behavioral approach to modeling residential mobility in the Prague metropolitan region. In *Proceedings of the 2015 Smart Cities Symposium Prague (SCSP'15)*, IEEE. DOI : <http://dx.doi.org/10.1109/SCSP.2015.7181552>
- [221] Carlos Caminha, Vasco Furtado, Vlória Pinheiro, and Caio Silva. 2016. Micro-interventions in urban transportation from pattern discovery on the flow of passengers and on the bus network. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI : [10.1109/ISC2.2016.7580776](https://doi.org/10.1109/ISC2.2016.7580776)
- [222] Chiara Boldrini, Raffaele Bruno, and Marco Conti. 2016. Characterising demand and usage patterns in a large station-based car sharing system. In *Proceedings of the 2016 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS'16)*, IEEE. DOI : [10.1109/INFOCOMW.2016.7562141](https://doi.org/10.1109/INFOCOMW.2016.7562141)
- [223] Zongjian He and Huijuan Zhang. 2014. Density adaptive urban data collection in vehicular sensor networks. *Journal of Networks* 9, 8 (August 2014), 1993–2002.
- [224] Guande Qi, Gang Pan, Shijian Li, Zhaohui Wu, Daqing Zhang, Lin Sun, and Laurence T. Yang. 2013. How long a passenger waits for a vacant taxi—Large-scale taxi trace mining for smart cities. In *Proceedings of the 2013 IEEE International Conference on Green Computing and Communications (GreenCom), Internet of Things (iThings/CPSCOM) and IEEE Cyber, Physical and Social Computing*, IEEE. DOI : <https://doi.org/10.1109/GreenCom-iThings-CPSCOM.2013.175>
- [225] Florian Hagenauer, Christoph Sommer, Simon Merschjohann, Takamasa Higuchi, Falko Dressler, and Onur Altintas. 2016. Cars as the base for service discovery and provision in highly dynamic networks. In *Proceedings of the 2016 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS'16)*, IEEE. DOI : [10.1109/INFOCOMW.2016.7562101](https://doi.org/10.1109/INFOCOMW.2016.7562101)
- [226] David Bogataj, Marija Bogataj, and Domen Hudoklin. 2017. Mitigating risks of perishable products in the cyber-physical systems based on the extended MRP model. *International Journal of Production Economics* 193 (2017), 51–62.
- [227] Luis Sanchez, Ignacio Elicegui, Javier Cuesta, and Luis Munoz. 2014. On the energy savings achieved through an internet of things enabled smart city trial. In *Proceedings of the 2014 IEEE International Conference on Communications (ICC'14)*, IEEE, 3836–3841. DOI : <http://dx.doi.org/10.1109/ICC.2014.6883919>
- [228] Luis Sanchez, Luis Muñoz, Jose A. Galache, Pablo Sotres, Juan R. Santana, Veronica Gutierrez, Rajiv Ramdhany, Alex Gluhak, Srdjan Krco, Evangelos Theodoridis, and Dennis Pfisterer. 2014. SmartSantander: IoT experimentation over a smart city testbed. *Computer Networks* 61, (March 2014), 217–238. DOI : <http://dx.doi.org/10.1016/j.bjp.2013.12.020>
- [229] Paolo Bellavista. 2011. Pervasive computing at scale: Challenges and research directions. In *Proceedings of the 2011 IEEE Sensors Conference*. IEEE. DOI : <http://dx.doi.org/10.1109/ICSENS.2011.6127000>
- [230] Dario Bonino, Maria T. Delgado Alizo, Alexandre Alapetite, Thomas Gilbert, Mathias Axling, Helene Udsen, Jose A. Carvajal Soto, and Maurizio Spirito. 2015. ALMANAC: Internet of things for smart cities. In *Proceedings of the 3rd International Conference on Future Internet of Things and Cloud (FiCloud'15)*, IEEE. DOI : <http://dx.doi.org/10.1109/FiCloud.2015.32>
- [231] Dario Bruneo, Salvatore Distefano, Francesco Longo, and Giovanni Merlino. 2016. An IoT testbed for the software defined city vision: The #smartme project. In *Proceedings of the 2016 IEEE International Conference on Smart Computing (SMARTCOMP'16)*, IEEE. DOI : [10.1109/SMARTCOMP.2016.7501678](https://doi.org/10.1109/SMARTCOMP.2016.7501678)
- [232] Sergio Consoli, Aldo Gangemi, Andrea G. Nuzzolese, Silvio Peroni, Valentina Presutti, Diego R. Recupero, and Daria Spampinato. 2014. Geolinked open data for the municipality of catania. In *Proceedings of the 4th International Conference on Web Intelligence, Mining and Semantics (WIMS'14)*. ACM, New York. DOI : <http://dx.doi.org/10.1145/2611040.2611092>
- [233] David Lorenzi, Jaideep Vaidya, Basit Shafiq Lahore, Soon Chun, Neelima Vegesna, Zamil Alzamil, Nabil Adam, Seth Wainer, and Vijayalakshmi Atluri. 2014. Utilizing social media to improve local government responsiveness. In *Proceedings of the 15th Annual International Conference on Digital Government Research (dg.o'14)*, ACM, New York, 236–244. DOI : <https://doi.org/10.1145/2612733.2612773>

- [234] Paolo Suppa and Eugenio Zimeo. 2016. A context-aware mashup recommender based on social networks data mining and user activities. In *Proceedings of the 2016 IEEE International Conference on Smart Computing (SMARTCOMP'16)*, IEEE. DOI : [10.1109/SMARTCOMP.2016.7501672](https://doi.org/10.1109/SMARTCOMP.2016.7501672)
- [235] Pierangelo Massa and Michele Campagna. 2014. Social media geographic information: Recent findings and opportunities for smart spatial planning. In *Proceedings of the 8th International Conference INPUT Smart City – Planning for Energy, Transportation and Sustainability of the Urban System*. TeMA Journal of Land Use Mobility and Environment, 645–658. DOI : <http://dx.doi.org/10.6092/1970-9870/2500>
- [236] Huina Mao, Gautam Thakur, and Budhendra Bhaduri. 2016. Exploiting mobile phone data for multi-category land use classification in Africa. In *Proceedings of the 2nd ACM SIGSPATIAL Workshop on Smart Cities and Urban Analytics (UrbanGIS'16)*, Article No. 9, ACM, New York. DOI : <https://doi.org/10.1145/3007540.3007549>
- [237] James Davey, Florian Mansmann, Jorn Kohlhammer, and Daniel Keim. 2012. Visual analytics: Towards intelligent interactive internet and security solutions. *The Future Internet*, F. Alvarez et al. (Eds.), Lecture Notes in Computer Science Vol. 7281, Springer, 93–104. DOI : http://dx.doi.org/10.1007/978-3-642-30241-1_9
- [238] Maryam Pouryazdan and Burak Kantarci. 2016. The smart citizen factor in trustworthy smart city crowdsensing. *IT Professional* 18, 4 (July–August 2016), 26–33. DOI : [10.1109/MITP.2016.72](https://doi.org/10.1109/MITP.2016.72)
- [239] Antonio Corradi, Luca Foschini, Leo Gioia, and Raffaele Ianniello. 2016. Leveraging communities to boost participation and data collection in mobile crowd sensing. In *Proceedings of the 2016 IEEE Global Communications Conference (GLOBECOM'16)*, IEEE. DOI : [10.1109/GLOCOM.2016.7841952](https://doi.org/10.1109/GLOCOM.2016.7841952)
- [240] Antonio Corradi, Giovanni Curatola, Luca Foschini, Raffaele Ianniello, and Carlos Roberto De Rolt. 2015. Smartphones as Smart Cities Sensors: MCS scheduling in the participact project. In *Proceedings of the 2015 IEEE Symposium on Computers and Communication (ISCC'15)*, IEEE Computer Society, 222–228. DOI : <https://doi.org/10.1109/ISCC.2015.7405520>
- [241] Ioannis Boutsis, Vana Kalogeraki, and Dimitrios Gunopoulos. 2016. Reliable crowdsourced event detection in smart cities. In *International Workshop on Science of Smart City Operations and Platforms Engineering (SCOPE) in partnership with Global City Teams Challenge (GCTC) (SCOPE-GCTC)*, IEEE. DOI : <https://doi.org/10.1109/SCOPE.2016.7515060>
- [242] Verónica Gutiérrez, Jose A. Galache, Luis Sánchez, Luis Muñoz, José M. Hernández-Muñoz, Joao Fernandes, and Gutier M. Presser. 2013. SmartSantander: Internet of things research and innovation through citizen participation. *The Future Internet*, A. Galis and A. Gavras (Eds.), Lecture Notes in Computer Science Vol. 7858, Springer, Berlin. DOI : http://dx.doi.org/10.1007/978-3-642-38082-2_15
- [243] Nazli Farajidavar, Sefki Kolozali, and Payam Barnaghi. 2016. Physical-cyber-social similarity analysis in smart cities. In *Proceedings of the 2016 IEEE 3rd World Forum on Internet of Things (WF-IoT'16)*, IEEE. DOI : [10.1109/WF-IoT.2016.7845473](https://doi.org/10.1109/WF-IoT.2016.7845473)
- [244] Giuseppe Cardone, Andrea Cirri, Antonio Corradi, Luca Foschini, Raffaele Ianniello, and Rebecca Montanari. 2014. Crowdsensing in urban areas for city-scale mass gathering management: Geofencing and activity recognition. *IEEE Sensors Journal* 14, 12 (December 2014), 4185–4195. DOI : <http://dx.doi.org/10.1109/JSEN.2014.2344023>
- [245] Giuseppe Cardone, Luca Foschini, Paolo Bellavista, Antonio Corradi, Cristian Borcea, Manoop Talasila, and Reza Curtmola. 2013. Fostering participation in smart cities: A geo-social crowdsensing platform. *IEEE Communications Magazine* 51, 6 (June 2013), 112–119. DOI : <http://dx.doi.org/10.1109/MCOM.2013.6525603>
- [246] Luca Cagliero, Tania Cerquitelli, Silvia Chiusano, Pierangelo Garino, Marco Nardone, Barbara Pralio, and Luca Venturini. 2015. Monitoring the citizens' perception on urban security in smart city environments. In *Proceedings of the 31st IEEE International Conference on Data Engineering Workshops (ICDEW'15)*, IEEE, 112–116. DOI : <http://dx.doi.org/10.1109/ICDEW.2015.7129559>
- [247] Antonio J. Jara, Yann Bocchi, and Dominique Genoud. 2014. Social internet of things: The potential of the internet of things for defining human behaviours. In *Proceedings of the 2014 International Conference on Intelligent Networking and Collaborative Systems (INCoS'14)*, IEEE Computer Society, 581–585. DOI : <http://dx.doi.org/10.1109/INCoS.2014.113>
- [248] M. Ma, S. Masud Preum, W. Tarneberg, M. Ahmed, M. Ruiters, and J. Stankovic. 2016. Detection of runtime conflicts among services in smart cities. In *Proceedings of the 2016 IEEE International Conference on Smart Computing (SMARTCOMP'16)*, IEEE. DOI : [10.1109/SMARTCOMP.2016.7501688](https://doi.org/10.1109/SMARTCOMP.2016.7501688)
- [249] Kassio Machado, Azzedine Boukerche, Pedro O. S. Vaz de Melo, Eduardo Cerqueira, and Antonio A. F. Loureiro. 2016. Exploring seasonal human behavior in opportunistic mobile networks. In *Proceedings of the 2016 IEEE International Conference on Communications (ICC'16)*, IEEE. DOI : <http://dx.doi.org/10.1109/ICC.2016.7510710>
- [250] Laura Lenz, Andre Pomp, Tobias Meisen, and Sabina Jeschke. 2016. How will the internet of things and big data analytics impact the education of learning-disabled students? A concept paper. In *Proceedings of the 3rd MEC International Conference on Big Data and Smart City (ICBDSC'16)*, IEEE. DOI : [10.1109/ICBDSC.2016.7460388](https://doi.org/10.1109/ICBDSC.2016.7460388)
- [251] John Soldatos, Moez Draief, Craig Macdonald, and Iadh Ounis. 2012. Multimedia search over integrated social and sensor networks. In *Proceedings of the 21st International Conference on World Wide Web (WWW'12 Companion)*, ACM, New York, 283–286. DOI : <https://doi.org/10.1145/2187980.2188029>

- [252] Dmitry Namiot and Manfred Sneps-Sneppe. 2013. Wireless networks sensors and social streams. In *Proceedings of the 27th International Conference on Advanced Information Networking and Applications Workshops (WAINA'13)*, IEEE, 413–418. DOI : <http://dx.doi.org/10.1109/WAINA.2013.27>
- [253] Michael G. Solomon, Vaidy Sunderam, Li Xiong, and Ming Li. 2016. Enabling mutually private location proximity services in smart cities: A comparative assessment. In *Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2'16)*, IEEE. DOI : [10.1109/ISC2.2016.7580757](https://doi.org/10.1109/ISC2.2016.7580757)
- [254] Luca Lugaric, Slavko Krajcar, and Zdenko Simic. 2010. Smart city—Platform for emergent phenomena power system testbed simulator. In *Proceedings of the 2010 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe'10)*, IEEE. DOI : [http://dx.doi.org/10.1109/ISGTEUROPE.2010.5638890](https://doi.org/10.1109/ISGTEUROPE.2010.5638890)
- [255] Luca Venturini and Elena Baralis. 2016. A spectral analysis of crimes in san francisco. In *Proceedings of the 2nd ACM SIGSPATIAL Workshop on Smart Cities and Urban Analytics (UrbanGIS'16)*, Article No. 4, ACM, New York. DOI : <https://doi.org/10.1145/3007540.3007544>
- [256] Agusti Solanas, Constantinos Patsakis, Mauro Conti, Ioannis S. Vlachos, Victoria Ramos, Francisco Falcone, Octavian Postolache, Pablo A. Pérez-Martínez, Roberto Di Pietro, Despina N. Perrea, and Antoni Martínez-Ballesté. 2014. Smart Health: A context-aware health paradigm within smart cities. *IEEE Communications Magazine* 52, 8 (August 2014), 74–81. DOI : <http://dx.doi.org/10.1109/MCOM.2014.6871673>
- [257] Awais Ahmad, Anand Paul, Mazhar Rathore, and Hangbae Chang. 2016. Smart cyber society: Integration of capillary devices with high usability based on cyber-physical system. *Future Generation Computer Systems* 56, (March 2016), 493–503. DOI : <http://dx.doi.org/10.1016/j.future.2015.08.004>
- [258] Deloitte. 2017. What Is Digital Economy? Retrieved October 2017 from <https://www2.deloitte.com/mt/en/pages/technology/articles/mt-what-is-digital-economy.html>.
- [259] Guyuan Chen, Chao Wang, Fuqiang Liu, Feng Wang, Shun Li, and Mingxiang Huang. 2016. Estimate of public environment-emotional index based on micro-blog data. In *Proceedings of the 2016 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*, IEEE. DOI : [10.1109/iThings-GreenCom-CPSCom-SmartData.2016.176](https://doi.org/10.1109/iThings-GreenCom-CPSCom-SmartData.2016.176)
- [260] Jorge Lanza, Luis Sánchez, Luis Muñoz, José Antonio Galache, Pablo Sotres, Juan R. Santana, and Verónica Gutiérrez. 2015. Large-scale mobile sensing enabled internet-of-things testbed for smart city services. *International Journal of Distributed Sensor Networks* (2015), Article ID 785061, 15 pages. DOI : <http://dx.doi.org/10.1155/2015/785061>
- [261] Davide Carboni, Antonio Pintus, Andrea Piras, Alberto Serra, Atta Badii, and Marco Tiemann. 2013. Scripting a smart—The cityscripts experiment in Santander. In *Proceedings of the 27th International Conference on Advanced Information Networking and Applications Workshops (WAINA'13)*, IEEE Computer Society, 1265–1270. DOI : <http://dx.doi.org/10.1109/WAINA.2013.85>
- [262] Eleni Fotopoulou, Anastasios Zafeiropoulos, Dimitris Pappaspyros, Panagiotis Hasapis, George Tsiolis, Thanasis Bouras, Spyros Mouzakitis, and Norma Zanneti. 2015. Linked data analytics in interdisciplinary studies: The health impact of air pollution in urban areas. *IEEE Access* 4 (December 2015), 149–164. DOI : <http://dx.doi.org/10.1109/ACCESS.2015.2513439>
- [263] Subhav Pradhan, Abhishek Dubey, Sandeep Neema, and Aniruddha Gokhale. 2016. Towards a generic computation model for smart city platforms. In *1st International Workshop on Science of Smart City Operations and Platforms Engineering (SCOPE) in partnership with Global City Teams Challenge (GCTC) (SCOPE-GCTC)*, IEEE. DOI : <https://doi.org/10.1109/SCOPE.2016.7515059>
- [264] Carlos Roberto De Rolt, Rebecca Montanari, Marcelo L. Brocardo, Luca Foschini, and Julio da Silva Dias. 2016. COLLEGA middleware for the management of participatory mobile health communities. In *Proceedings of the 2016 IEEE Symposium on Computers and Communication (ISCC'16)*, IEEE. DOI : [10.1109/ISCC.2016.7543867](https://doi.org/10.1109/ISCC.2016.7543867)
- [265] Roberto Gimenez, Diego Fuentes, Emilio Martin, Diego Gimenez, and Judith Pertejo. 2012. The safety transformation in the future internet domain. *The Future Internet*, F. Alvarez et al. (Eds.), Lecture Notes in Computer Science Volume 7281. Springer, 190–200. DOI : http://dx.doi.org/10.1007/978-3-642-30241-1_17
- [266] Yibin Li, Wenyun Dai, Zhong Ming, and Meikang Qiu. 2016. Privacy protection for preventing data over-collection in smart city. *IEEE Transactions on Computers* 65, 5 (May 2016), 1339–1350. DOI : <http://dx.doi.org/10.1109/TC.2015.2470247>
- [267] Burak Kantarci and Hussein T. Mouftah. 2014. Trustworthy sensing for public safety in cloud-centric internet of things. *IEEE Internet of Things Journal* 1, 4 (August 2014). DOI : <http://dx.doi.org/360-368>. [10.1109/JIOT.2014.2337886](https://doi.org/10.1109/JIOT.2014.2337886)
- [268] Jie Li, Zhaolong Ning, Behrouz Jedari, Feng Xia, Ivan Lee, and Amr Tolba. 2016. Geo-social distance-based data dissemination for socially aware networking. *IEEE Access* 4 (April 2016), 1444–1453. DOI : <http://dx.doi.org/10.1109/ACCESS.2016.2553698>
- [269] E. Bellini, P. Ceravolo, and P. Besi. 2017. Quantify resilience enhancement of UTS through exploiting connect community and internet of everything emerging technologies. *ACM Transactions on Internet Technology* 9, 4 (2017), Article 39.

- [270] Joaquim Massana, Carles Pous, Llorenç Burgas, Joaquim Melendez, and Joan Colomer. 2017. Identifying services for short-term load forecasting using data driven models in a smart city platform. *Sustainable Cities and Society* 28, 108–117.
- [271] Kaile Zhou, Changhui Yang, and Jianxin Shen. 2017. Discovering residential electricity consumption patterns through smart-meter data mining: A case study from China. *Utilities Policy* 44 (2017), 73–84.
- [272] B. Lin, Y. Huangfu, N. Lima, B. Lamb, and D. J. Cook. 2017. Analyzing the relationship between human behavior and indoor air quality. *Journal of Sensor and Actuator Networks* 6, 3 (2017), 13–27.
- [273] T. Li. 2017. Criminal behavior analysis method based on data mining technology. In *Proceedings of the International Conference on Smart City and Systems Engineering (ICSCSE'16)*, 562–565.
- [274] Md Ilea Pramanik, Raymond Y. K. Lau, Haluk Demirkan, and Md. Abul Kalam Azad. 2017. Smart health: Big data enabled health paradigm within smart cities. *Expert Systems With Applications* 87 (2017), 370–383.
- [275] Nalavadi Srikantha, Khaja Moinuddin, Lokesh K S and Aswatha Narayana. 2017. Waste management in IoT-enabled smart cities: A survey. *International Journal of Engineering and Computer Science* 6, 5 (2017), 21507–21512. DOI: [10.18535/ijecs/v6i5.53](https://doi.org/10.18535/ijecs/v6i5.53)
- [276] A. Fernández-Ares, A. M. Mora, M. G. Arenas, P. García-Sánchez, G. Romero, V. Rivas, P. A. Castillo, and J. J. Merelo. 2017. Studying real traffic and mobility scenarios for a smart city using a new monitoring and tracking system. *Future Generation Computer Systems* 76 (2017), 163–179.
- [277] Pierfrancesco Bellini, Daniele Cenni, Paolo Nesi, and Irene Paoli. 2017. Wi-Fi based city users' behaviour analysis for smart city. *Journal of Visual Languages & Computing* (in press).
- [278] Ivana Semanjski, Sidharta Gautama, Rein Ahas, and Frank Witlox. 2017. Spatial context mining approach for transport mode recognition from mobile sensed big data. *Computers, Environment and Urban Systems* 66 (2017), 38–52.
- [279] Matteo Manca, Ludovico Boratto, Victor Morell Roman, Oriol Martori i Gallissà, and Andreas Kaltenbrunner. 2017. Using social media to characterize urban mobility patterns: State-of-the-art survey and case-study. *Online Social Networks and Media* 1 (2017), 56–69.
- [280] A. Shields, P. Doody, and T. Scully. 2017. Application of multiple change point detection methods to large urban telecommunication networks. In *Proceedings of the 28th Irish Signals and Systems Conference (ISSC'17)*.
- [281] M. Jahnke, L. Ding, K. Karja, and S. Wang. 2017. Identifying origin/destination hotspots in floating car data for visual analysis of traveling behavior. *Lecture Notes in Geoinformation and Cartography*. Springer, 253–269.
- [282] Yongxin Liu, Xiaoxiong Weng, Jiafu Wan, Xuejun Yue, Houbing Song, and Athanasios V. Vasilakos. 2017. Exploring data validity in transportation systems for smart cities. *IEEE Communications Magazine* 55, 5 (2017), 26–33.
- [283] C. G. Cassandras. 2017. Online control and optimization for cyber-physical systems. In *Cyber-Physical Systems Foundations, Principles and Applications*, Song et al. (Eds). Elsevier, Amsterdam, 31–52.

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