CityDNA Dynamics: A Model for Smart City Maturity and Performance Benchmarking

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ABSTRACT

Smart cities have emerged significantly since their initial appearance in 1990s, more and more cities around the world are striving to gain intelligence and in this regard the need for standardization and performance measurement grows. Given the current challenges in the field of smart cities, this work revisits the proposed *"cityDNA"* framework which has been designed to detect the interrelations between smart city dimensions and form city profile. This work contribute to further enable benchmarking and measuring the maturity of smart cities through the exploitation of international standards and civil engagement. The proposed framework along with the design of a web application will handle urban data effectively. "cityDNA" that will be advanced to receive and utilize urban data and visualize cities' health and maturity metrics is presented, while potential constraints on its implementation are highlighted.

CCS CONCEPTS

• **Human-centered computing** → Visualization; Visualization application domains; Information visualization; • **Applied computing** → Computers in other domains; Computing in government; • **Information systems** → Information systems applications; Decision support systems; Data analytics; World Wide Web; Web applications; Crowdsourcing.

KEYWORDS

smart cities, artificial intelligence, cityDNA, city profile, citizen engagement, city benchmarking, maturity, conceptual model, standardization

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1 INTRODUCTION

The high rate of urbanization and the need to save valuable resources and protect the environment at national and international level have led to the invention of the vision of smart cities (SC). The rapid developments in information and communication technologies (ICTs) and the particular interest of many governments, international organizations, academia and industries in digital transformation of cities have been the driving force behind this vision. Due to their interdisciplinarity, SC have attracted scholars from various research fields, resulting in the development of many approaches, architectures and models for their design and implementation [1]-[5]. In addition, local policymakers, after investigating urban needs, following technological advancements and adopting best practices that have been successfully implemented, attempted to design and provide innovative and user-friendly services to their citizens [5]. Many companies, such as IBM[1], Cisco[2], Libelium[3], etc. have also moved in the same direction, designing and developing new products and services for cities. This trend generates an emerging SC market, which -according to International Data Corporation[4] (IDC) Worldwide Smart Cities Spending Guide- is estimated to approximately US $124 billion in 2020, up 18.9% from 2019.

One of the most popular model used to describe SC was that of [6], which described the city as a six-dimensional system [2, 3, 5]. Moustaka et al. [5], adopting the aforementioned model in their work, have found that the majority of services, designed and developed till 2017, focused mainly on the dimensions of mobility and the environment, while several scholars involved in improving the quality of life and strengthening citizen engagement. In the following years, there has been a shift from smart dimensions to smart services, such as smart health, smart food, etc. [7, 8], while the interest of several scholars turned to studying and addressing social and ethical issues that have emerged in cities, such as behavior analysis, security and privacy protection, etc. [9]-[11].

The determination of the requirements and decision making on the design and implementation of services that will turn a city into a SC, require the acquisition of profound knowledge that is lying

[1]https://www.ibm.com/
[2]https://www.cisco.com/
[3]http://www.libelium.com/
[4]https://www.idc.com/getdoc.jsp?containerId=prUS46016320

in every aspect of urban life and is changing daily. The acquisition of knowledge, in turn, requires appropriate data collection infrastructures as well as efficient analytical methods that will lead to exploitable conclusions and patterns. According to a recent literature review [5], it has emerged that Internet of Things (IoT) and crowdsourcing are the main urban data sources, while several cities provide open data to stakeholders (scholars, developers, etc.) to contribute to the development of smart services and enhance government transparency. Regarding the data analytics, statistical methods, data-, text- and semantic web-mining, as well as supervised learning and visualization techniques were exploited [5]. Moreover, the promising artificial intelligence (AI) with its dynamics is a powerful weapon in addressing the open urban challenges, while creating high expectations for living standards in SC [12]-[14].

As SC evolve and mature, the need to standardize them and measure their effectiveness has arisen. In the context of standardization, several international and European standardization organizations, such as International Telecommunications Union[5] (ITU), International Standards Organization[6] (ISO, 2017), CEN[7], CENELEC[8] etc., have attempted to define and propose appropriate standards and key performance indicators (KPIs) to measure and evaluate the degree of smartness and sustainability achievement in cities. An essential prerequisite for the composition of these indicators is the existence and availability of appropriate data, which in this case comes from open data platforms developed by municipalities [15]. KPIs that can be used for internal (comparison between different indicators for the same city) or external (comparison between the same indicators for different cities) benchmarking constitute valuable decision-making metrics for SC stakeholders. However, as pointed out by [16], the selection of appropriate indicators is particularly difficult and is mainly determined by the purpose of their use. In this regard, some scholars and companies have designed and proposed frameworks and tools to assist in selecting KPIs and measuring the performance and maturity of SC. Airaksinen et al. [15] developed a KPIs-driven performance measurement system for SC by utilizing city open data, while Christ et al. [17] presented a performance dashboard for municipalities benchmarking and suggested ways in which a SC can use ICT-derived data to improve the benchmarking process. In addition, TM Forum[9] has launched the SC Benchmark, an app based on BSI[10] aiming to enable SC stakeholders to find and share information and best practice between cities [18]. As concerns the measurement of maturity, Torihna and Machado [19] conducting research on existing maturity models of cities, concluded to the selection and evaluation of three models (i.e., IDC Smart City Maturity Model (SCMM), Brazilian (SCMM) and Sustainability Outlook (SCMM)) that describe the cities in a holistic way. Finally, Warnecke et al. [20] proposed a maturity model and web-based self-assessment tool for benchmarking cities.

[5]http://www.itu.int/en/ITU--T/focusgroups/ssc/Pages/default.aspx.
[6]https://www.en-standard.eu/iso-standards/?gclid=EAIaIQobChMI48ae5-ac5wIVRbTtCh2CigbZEAAYAiAAEgIPoPD_BwE
[7]https://www.cen.eu/Pages/default.aspx
[8]https://www.cenelec.eu/
[9]https://www.tmforum.org/
[10]https://www.bsigroup.com/

Taking into account the evolution of smart cities and the current state of affairs that focuses on benchmarking cities and measuring their maturity, this article aims to propose a novel framework combined with an application that will generate cities' profiles, providing valuable insights on their health and maturity. The proposed framework constitutes a redesigned version of the "*cityDNA*" framework presented in our previous work [21].

The previous approach to the *"cityDNA"* model [21] followed the SC model that was introduced by Giffinger and Gudrun [6]. This first approach dealt with the investigation and identification of potential interrelations between the SC dimensions, in an attempt to shape the SC profiles and to facilitate city monitoring and policy making. Although the concept of the model was promising, the low level of maturity of the smart cities, the lack of sufficient and real-time data and the lack of standardization in previous years, hampered its development. The maturation of smart cities and current advancements in the field of standardization and urban data production have led to the redesign of the *"cityDNA"* framework. Following the *ISO 37120 Standard*[11] the *ITU-T Y.4903/L.1603 Recommendation*[12] and the *ITU-T Y.4904/L.1604 Recommendation*[13] for measuring city performance and smart city maturity, the revisited framework, along with a web application aspire, can assist in the production of the appropriate urban data and to visualize the city's profile. Specifically, the use of cutting-edge technologies for its development can enable "*cityDNA*" to collect KPI-driven urban data, and health and maturity benchmarking in SC.

The contribution of this article is three-fold: i) addresses the limitations on the utilization of available urban data and points out the need to strengthen citizens' participation in the production of urban data required for SC formulation, ii) discusses AI's contribution to knowledge acquisition, predicting future situations, and consequently the decision-making process and iii) presents a novel framework and outlines a web application that will be developed, aiming at activating citizens to produce urban data and visualizing SC health and maturity metrics. The proposed framework, along with a web application, is expected to enhance citizen engagement and benefit SC stakeholders.

The rest of this article is organized as follows: *Section 2* deals with the limitations of urban data exploitation in the composition of KPIs, suggesting as a countermeasure to enhance the citizens' involvement in SC in terms of urban production data. The exploitation of AI technologies in SC is discussed in *Section 3*, while the *"cityDNA"* framework along with an application that leverages citizen-generated data and AI technologies to facilitate decision-making and urban planning, which is in the development phase, is presented in *Section 4*. Finally, *Section 5* contains some conclusions and future perspectives.

2 CITIZENS AS "LOCAL DATA FEEDERS"

Knowledge discovery activities and the synthesis of KPIs require the existence and availability of urban data that meet the 5Vs of Big Data, which make them suitable for modeling and knowledge

[11]https://www.iso.org/standard/68498.html,
[12]https://www.itu.int/rec/T-REC-L.1603/en
[13]https://www.itu.int/rec/T-REC-Y.4904/en

extraction [22]. Unfortunately at present, there are two issues concerning the availability of urban data that must be addressed: i) urban data that is available for exploitation is mainly provided by municipalities through open data platforms and usually does not meet the 5Vs, since data sources are limited, the way they are collected is not always in line with specific technical specifications, and ii) the available data does not always provide the information necessary for the composition of the indicators, since many cities do not follow the guidelines of a standard [15]. As regards the second issue, the World Council on City Data (WCCD) has striven to standardize the provision of urban data by the municipalities, by developing the first *ISO 37120 certification system* and the *Global Cities Registry*. In addressing the first issue, given the constraints of the cities' resources on the development and maintenance of data collection infrastructures, taking advantage of citizens and crowdsourcing methods [23] is recommended [11].

Citizens are undoubtedly the main pillar of cities since they form cities and live in them. For this reason, many scholars have defined and dealt with the dimension of smart people, highlighting the value of citizen engagement in realizing the vision of SC [1, 2, 11, 24]-[26]. In the context of public participation, citizens act as "prosumers" of geo-tagged data and content affecting cities' everyday norms and interactions [27, 28]. The content generated by them, known as *user-generated content (UGC)* or *user-created content (UCC)* (OECD, 2006), is produced in three different user-centric ways, which are the following: i) *participatory sensing* [29], ii) *opportunistic sensing* [30], and iii) *opportunistic mobile social networks* [31]. The findings of a recent review on the exploitation of UGC in SC have revealed that participating sensing is the most common way of creating UGC in SC [32]. This preference is due to both the efficiency and the maturity level of participating sensing compared to the other two ways of generating UGC, since the task of sensing is assigned to a specific "crowd" of people and the content to be created is fully specified.

3 ARTIFICIAL INTELLIGENCE IMPACT ON CITIES TRANSFORMATIONS

AI, which was first coined by John McCarthy in 1956, has been studied for decades and remains one of the most ambiguous topics since draws upon a variety of disciplines such as computer science, mathematics, linguistics, philosophy, psychology, neuroscience and many other fields [13, 33, 34]. Due to this fact, several definitions have been proposed to define the AI term [35, 36]. After analyzing the proposed definitions, Lagg and Hutter [36] came to the following definition which appears to be quite clear and comprehensive:

"Intelligence measures an agent's ability to achieve goals in a wide range of environments."

Of particular interest is also the following definition which was proposed by Kaplan and Haenlein [37] and highlights the value of data for acquiring knowledge and achieving goals.

> *"AI is a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation."*

Since the digital transformation of cities requires the data exploitation with the purpose of acquiring hidden urban knowledge, which is needed for decision making and strategy planning [5], it turns out that AI is the vehicle for the transition from conventional to SC. SI by providing machines with intelligence is expected to lead to the achievement of machine-to-machine communication and the complete and efficient automation of processes that required human intervention and valuable resources. Several scholars working in the field of SC have recognized the contribution of SI and used it in their research. In this respect Srivastava et al. [34] investigated and proposed some AI advanced solutions in combating critical threats to security and privacy in cities. Tools that use Artificial Neural Networks (ANNs) and systems based on behavioral analysis and AI, such as AISight and drones, contribute effectively to the identification and decision-making to address these threats. Focusing on safeguarding and enhancing privacy in smart energy systems in SC, Alamaniotis et al. [38] have also designed an innovative methodology that exploits particle swarm optimization.

On the other hand, Paz et al. [39] focusing on the control and intelligent management of public lighting with the purpose of both energy saving and achieving the maximum visual comfort in illuminated areas, have designed an adaptive architecture which exploits various techniques of AI (ANN, Service Oriented Approach (SOA), multi-agent systems (MAS), EM algorithm, etc.). In addition, Nigon et al. [13] have investigated how Multi-Agent Systems (MAS) can be exploited in energy management in SC. In particular, they have adopted a bottom-up approach based on AMOEBA (Agnostic Builder by Self Adaptation) - a multi-agent AI system - with the aim of achieving real-time energy management at three levels: i) city level: renewable energy production, ii) building level: improving energy efficiency in buildings, and iii) individual level: achieving human well-being in daily life. Of particular interest is also the work of Khan et al. [40], who proposed the BluWave-ai framework that leverages the Internet of Things (IoT) and deep learning techniques to optimize the benefits offered by microgrids, which are more efficient than mainstream electrical utilities grids.

Beyond the areas of security and energy, AI has been used to improve the quality of life in cities. Specifically, a waste collection management system which utilize IoT and offers intelligence to waste bins, was developed and tested by Shyam et al. [41] in India. Furthermore, a novel deep learning model which based on Long Short Term Memory (LSTM) networks was designed by Kök et al. [42] aiming at predicting future values of air quality in cities. Finally, Allam and Dhunny [12] intending to help policymakers increase the liveability of the urban fabric and enhance economic growth and opportunities, proposed a methodology that leverages AI and secures the integration of governance, culture and metabolism.

4 "CITYDNA" REVISITED: A CITY MATURITY AND PERFORMANCE TRACKING TOOL

All style elements are specified in this template to facilitate the production of your paper and to have the styles consistent throughout. Taking into account the evolution of SC and the current challenges related to the production and efficient utilization of urban data, standardization, benchmarking and measuring the maturity of cities, the idea of the *"cityDNA"* model [21] came back to the forefront. This model, inspired by Biology and human, considers the city to be a living organism whose life and evolution are shaped by multiple interactions and reciprocities. Just as the human DNA provides information about human health that changes with time as the body matures [43], so the *"cityDNA"* will provide information on the city health and its evolution.

The proposed framework, which is presented in Fig. 1, will be based on the following main principles and characteristics:

(i) will assume that the city is a *living organism* that inherits its past (economy, environment, culture, society) and shapes its future based on its current conditions (infrastructures) and choices (planning);
(ii) will exploit the *ISO 37120:2014 standard* [44], which specifies the KPIs for smart sustainable cities (SSC), considering that cities consist of three main smart dimensions: economy, environment, society and culture;
(iii) will exploit the *ISO 37153:2017 standard* [45] which specifies the maturity model for SC assessment and improvement;
(iv) will adopt the model of *"cityDNA"* [21] to visualize the health and maturity of the city.

The core of the *"cityDNA"* framework will be a web application, in which data will be input, rules will be applied to analyze this data that will lead to knowledge acquisition, and the gained insights will be visualized and offered to SC stakeholders. Specifically, heterogeneous data retrieved from various data sources such as IoT, municipalities' open data platforms, crowdsourcing activities, etc. will be entered into the application via a rule-based uploader to allow selective data entry and the data to be suitable for the synthesis of KPIs. Since citizen engagement is one of the key objectives of the proposed framework, citizens and their UGC will be the main urban data source to be utilized (Fig. 1). Then, the health and maturity level of SC will be determined and the interactions between three SC dimensions will be investigated through the exploitation of the processed data, the KPIs specified by ISO 37120 and the maturity model specified by ISO 37153 [44, 45]. The data processing and analysis that will lead to the acquisition of profound knowledge will be carried out through the exploitation of AI technologies. The outcomes of the analysis and data synthesis will be displayed and presented in "cityDNA" format on a dashboard, which will be available to SC stakeholders. The shape of "cityDNA" helix (i.e., green: healthy cityDNA, red: mutated cityDNA) and its evolution over time will reveal the state of health and maturity of the city, while the KPI values and the correlations between the SC dimensions will be presented in detail.

As regards the development and implementation of the proposed framework, there are two main limitations that must be taken into account and addressed. The first one concerns the limited availability of real-time urban data which are necessary to obtain reliable information through the "cityDNA" helix. The second limitation concerns the protection of personal data and privacy of individuals who will participate in crowdsourcing activities for the production of urban data. With the purpose of addressing the first limitation, historical or periodic data coming from municipalities' open data platforms (e.g., ANALYSE BOSTON, LONDON DATASTORE, etc.) will be used in the development of the application, and then this data will be enriched with real-time data coming from crowdsourcing activities. Concerning the second limitation, the *General Data Protection Regulation (GDPR)* [46] will be fully implemented in order to fully protect users' privacy and to enhance information security in SC.

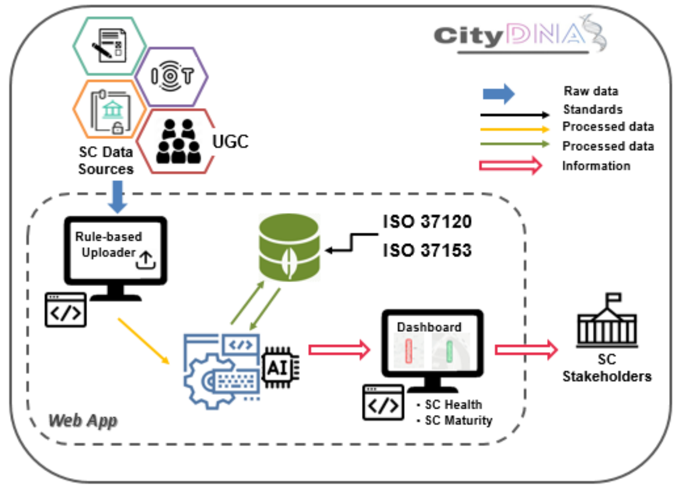

Figure 1: The "cityDNA" framework

5 CONCLUSIONS

This article, which considers that city is a living organism, proposes SC profiling by introducing the *"cityDNA"* framework, according to which, the health of a city and its evolution over time, as well as the correlations between its dimensions can to be captured and visualized. The *"cityDNA"* framework along with a web application, adopting ISO 37120 and ISO 37153 standards, aspires to enhance the production of urban data by crowdsourcing methods and generate cities' profiles with the purposes of SC health and maturity benchmarking, facilitating decision-making and empowering citizen engagement. The proposed framework and the web application which is at its design and prototyping phase were presented in detail and the potential limitations were discussed.

Our future thoughts concentrate on two directions. The first one concerns the implementation of the revisited *"cityDNA"* framework through the development of the proposed web application. The latter aims to further expand the proposed framework through the exploitation of advanced AI techniques to predict and manage future situations in SC.

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