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Article

Smart Cities from the Perspective of Systems

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Abstract: Modern cities are complex adaptive systems in which there is a lot of dependency and interaction between the various stakeholders, components, and subsystems. The use of digital Information and Communications Technology (ICT) has opened up the vision of smart cities in which the city dwellers can have a better quality of life and the city can be better organized and managed. The deployment of ICT solutions, however, does not automatically or invariably improve the quality of living of the citizens. Analyzing cities as complex systems with various interacting sub-systems can help us understand urban dynamics and the fate of smart cities. We will be able to analyze various policy interventions and ascertain their effectiveness and anticipate potential unintended consequences. In this paper, we discuss how smart cities can be viewed through the lens of systems thinking and complex systems and provide a comprehensive review of related techniques and methods. Along with highlighting the science of cities in light of historic urban modeling and urban dynamics, we focus on shedding light on the smart city complex systems. Finally, we will describe the various challenges of smart cities, discuss the limitations of existing models, and identify promising future directions of work.

Keywords: smart city; complex system; complexity; systems of sub-systems

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1. Introduction

From the mid-19th century till the early 20th century, the second industrial revolution in Britain, continental Europe, North America, and Japan increased commercial opportunities in cities, led to rapid urbanization causing increases in pollution, health problems, crime rate, safety issues, and concurrent burden on cities' resources. With increased interconnectivity in cities at an unprecedented pace, complexity surged and adverse repercussions emerged. Some of these undesirable side effects witnessed so far include crowd disasters, traffic jams, urban sprawl, etc. Climate change and financial crises are examples of some unintended consequences of unplanned urbanization [1]. The development of smart cities is a solution to resolve the aforementioned problems. For planning the smart city strategies and sustainable urban growth, advanced technology is used for providing services to the citizens and to manage the urban environment [2].

Over the past few decades, the concept of smart cities has passed through three phases: (i) improving the infrastructure of buildings; (ii) providing health safety and increasing efficiency; (iii) employment of Information and Communications Technology (ICT) solutions. ICT solutions were implemented to provide information services to civil, governmental, and private entities and break the barriers of sharing data among different entities [3]. At the end of the 1990s, with the advancement in modern technology, the focus of smart cities has centered on: instrumentation to strengthen the capacity of the instruments collecting information; interconnection to sustain the traffic of information; intelligence in data processing; and analysis of collected and transmitted data [4].

The rapid deployment of ICT led to massively interconnected elements of smart cities. These elements form a complex system and the emergent behavior of elements of any complex system cannot be understood in isolation as various subsystems interact with each other dynamically over a long time using non-linear interacting feedback loops [5,6]. Complexity science is not a single theory but an accumulation of various theories and conceptual tools from different disciplines [7]. In the 1950s, with the application of general system theory and cybernetics in social sciences, scholars formally started considering cities as a system. The basic idea behind this consideration was the concepts of controllers and feedback loops to steer the system for achieving desired goals. However, this consideration required more significant interventions than anything that had been presented before in the field of urban planning [8–10].

Spontaneous adaptation and organization of complex systems lead to emerging behaviors. To reap the benefits of this positive side of complex systems, we need to understand interactions among various dimensions of smart cities that give rise to emerging behaviors rather than individual components. This paper focuses on presenting a systems perspective on smart cities. Systems thinking is a versatile framework of tools that can be applied for diverse things such as predicting the sustainability of the global economic system [11], studying the educational ecosystem [12], analyzing causes of misinformation [13], or understanding cancer [14]. Our paper sheds light on the history of urban dynamics, modeling, and formulations to present system science of urban functioning and smart city as a complex system. In addition, we also examine the challenges, limitations, and future directions of smart cities as a complex system of sub-systems (SoS).

1.1. Smart City: Definition, Application, and Motivation

The vision of a smart city is to build an urban center that can provide safety, security, a nature-friendly environment, efficient health services, and economic growth to its citizens using advanced electronic devices and infrastructure. In smart cities, ICT solutions are used to collect information from several sources, such as citizens' devices, sensor networks, traffic, and other systems to develop applications that improve city services such as public health, disaster management, governance, public safety, environmental monitoring [1].

The concept of smart cities is not unique and has been described in various ways in the literature. It has become quite common in scientific literature and international policy during the past two decades to refer to a "smart city" [15]. Although the phrase is widely used, it is tough to keep up with a consensus on what it means. There is no one pattern for framing a smart city, nor is there a single definition of what constitutes a smart city that applies to all situations. According to International Telecommunications Union (ITU), there are more than 100 definitions of a smart city [16]. Hollands has explained that to develop a smart city, we have to implement the ICT solutions for economic and urban growth with the involvement of citizens and government [17]. Giffinger et al. have described the vision of a smart city as the implementation of smart mobility, economic growth, and the high living quality of citizens [18]. Hall has stated that to build a smart city, we have to provide security through monitoring, ensure a high quality of life, and integrate all infrastructures to optimize the resources and maintenance activities [19].

One of the primary reasons for the lack of agreement on what constitutes a "smart city" is that the phrase is being used for two distinct domains, namely, physical and soft infrastructure. Specifically, Neirotti et al. have demonstrated that ICT may play a significant role in the operations of systems in the hard domains such as buildings, energy grids, natural resources, water management, waste management, transportation, and logistics [20]. Education, culture, social inclusion, and governance are examples of soft domains where the use of ICT may not be as important as it is in hard domains [21].

Research conducted by the Vienna University of Technology's Center of Regional Science has identified six primary dimensions of a smart city, namely, smart economy, smart mobility, smart environment, smart people, smart living, and smart governance. These give a useful framework for selecting dimensions while keeping in mind the resources and ultimate aims of a specific city. We now explain briefly each of these dimensions:

- Smart Economy: innovative solutions linked to ICT in the labor market supporting a high level of productivity in cities [3].
- Smart Mobility: high-speed connection networks in a city with supporting ICT infrastructure.
- Smart Environment: optimized energy consumption with renewable energy sources.
- Smart People: a society open to learning and undertaking actions that contribute to the quality of life.
- Smart Living: access to social infrastructure, public services, cultural, technical, and leisure spaces.
- Smart Governance: optimal public administration and management between different agencies practicing technologies [22].

The development of a smart city requires proper planning and implementation of laws, policies, financial strategies, and ethical values under the umbrella of government. The role of government is not limited only to the implementation of laws. Taking the measures for checking the efficiency of each department, improvements in the quality of citizens' lifestyle, and keeping an eye on the lacking region are also the responsibilities of smart governance. If a department or a region shows a continuous downfall, they should reconsider the policies and laws for the specific area of concern. Transformation of the digital infrastructure according to the requirements is also necessary.

1.2. Contributions and Organization of This Paper

Multiple studies have been conducted on smart cities. However, our paper is unique in the following aspects:

- Our study is the first of its kind where we have highlighted the link and applications of urban models and theories for understanding smart cities as complex systems of sub-systems;
- To understand and define the functioning process of cities as complex systems, we discuss different types of urban dynamics and various systemic principles of urban functioning;
- We highlight the main development challenges of smart cities along with system-based challenges of cognition, testing, validation, heterogeneity, and the multitude of stakeholders that hinder the system models of a smart city;
- We also focus on the dynamic issues of smart cities and describe how understanding them as SoS can resolve these problems;
- Finally, we elaborate on the limitations of existing approaches and highlight various open research problems that require further development. The comparison of this paper with existing surveys is presented in Table 1.

Organization of paper: The organization of the paper is as follows. Section 2 presents a background from urban modeling, theories, and functioning of cities to smart cities and complex systems. Section 3 discusses smart cities as complex systems. Its subsections elaborate on the system of smart cities, use of system archetypes in smart city modeling, system theories, and application of theories and models in smart cities, along with system-based challenges. Section 4 elaborates on the potential pitfalls of modeling a smart city as a SoS. Section 5 presents future research directions and further elucidates the analytical discussion on the way forward. Finally, the paper is concluded in Section 6. The organization of this paper is illustrated in Figure 1.

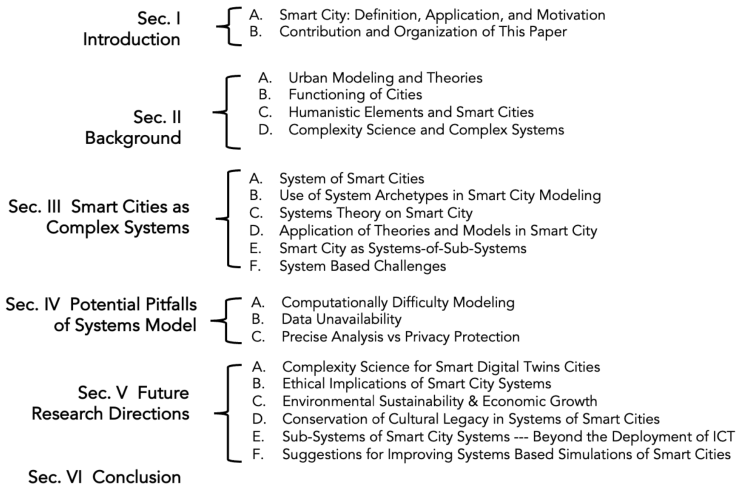


Figure 1. Illustration of paper organization.

Table 1. Comparison of the paper with existing surveys. Legends: ✓ = discussed, × = not discussed, ≈ = partially discussed, SC= smart cities, CS = Computer Science, IT = Information Technology, Dev = Development, SB = System-Based, Lim = Limitations, FD = Future Directions.

			Scope				Challenges			
Reference	**Year**	**Focused Area(s)**	**Urban Models and Theories for SC as Systems of Sub-Systems**	**Urban Dynamics and Systemic Functioning Principles in SC**	**Application of Theories and Models in SC**	**Beyond ICT Deployment Vision of SC**	**Dev**	**SB**	**Lim**	**FD**
Silva et al. [23]	2018	Overviews the features and implementations of SC	×	×	✓	×	✓	×	✓	✓
Camero and Alba [24]	2019	From and CS and IT lens presents a systematic analysis of SC	×	×	×	×	×	×	✓	×
Ismagilova et al. [25]	2019	From an information systems perspective synthesizes issues related to SC	×	×	×	×	✓	×	✓	✓
Corcuera et al. [26]	2019	Review of techniques and methods of building SC	×	×	✓	×	×	×	×	✓
Radu [27]	2020	Presents main disruptive technologies in SC	×	×	✓	×	✓	×	≈	≈
Habibzadeh et al. [28]	2020	Studies system design of SC	×	×	×	×	≈	×	✓	≈
This paper	2022	Systems perspective of SC	✓	✓	✓	✓	✓	✓	✓	✓

2. Background

This section presents the science of cities based on models and theories used to model the cities. These theories are based on the concept of equilibrium which is also discussed in detail in this section. This section also covers the major developmental challenges of smart cities along with the discussion of how ICT-focused solutions are affecting the smart cities. According to some researchers, foundations of highly developed cities are not just based on technical solution. In this context, this section also contains the idea of human, social, entrepreneurial, and infrastructural capital for smart cities. Additionally, background on smart cities and complexity is presented in this section.

2.1. Urban Models and Theories

The translation of functioning theory of cities into a mathematical model, calibration, and validation of model to develop algorithms is called urban modeling. Initially, cities were considered as stable structures observing development as a monocentric pattern around the peripheries of center dominant function. Urban models emerged through policy imperatives in the context of technologies making simulation possible, e.g., for solving transportation problems in cities.

Location theory, theories from geometry, and social physics dominated the equilibrium perspective in urban modeling. Optimization models based on location theory rely on urban economic models. Urban models inspired by social physics emerged through policy imperatives. On the contrary, spatial morphology used ideas of form and structure from geometry. The models become more descriptive, less problem-solving, and hence not policy-oriented.

Alonso, in 1964, was the first to formally construct an urban economic theory, known as the new urban economics. Isard et al. presented a practical method catalog based on ideas of spatial interaction inspired by macroeconomic models such as input–output analysis and social physics [8]. During the 1970s and 1980s, the aggregate static procedure to theorizing and modeling motivated the switch to disaggregate activities in which planning focused on bottom-up decentralized urban dynamics that deal with intrinsic processes of change such as chaos and bifurcation theory, examining rapid and chaotic cycles in urban phenomena. In the late 19th century, the agent-based approach shifted the focus to very micro-level agents [29]. Later, these ideas to incorporate emergent patterns inspired models to analyze systems within the system. Figure 2 shows the main features of cities, planning, and urban modeling, as highlighted in literature from the 18th to the late 20th century. In what follows, some of the main urban models are discussed.

2.1.1. Models Based on Location Theory

Location theory, which emerged in the late 19th century, is based on the principle of 'what is where'. 'What' deals with any possible economic activity comprising dwellings, stores, plants, or public facilities. 'Where' pertains to areas such as cities, neighborhoods, political authorities, or customs unions. The models based on location theory aim to demonstrate why specific economic activities prefer to settle themselves in distinct places.

2.1.2. Land-Use Transportation Models

This class of model is primarily concerned with the way employment and populations are located in urban areas. It also focuses on the spatial interactions between locations at a cross-section in time to simulate the city into equilibrium behaviors.

2.1.3. Spatial Interaction Model

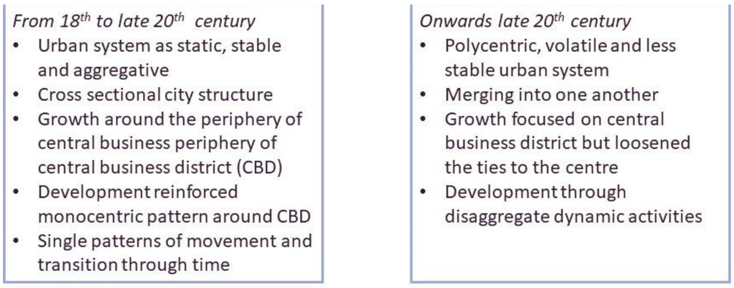
Using analogies from classical Newtonian physics, spatial interaction modeling captures non-linear logistic growth and involves interactions from movements between different spatial locations of people, goods, and information to migration between cities. Recently, physics has been used to contain ideas of complexity as exhibited in self-organization, scaling, and far-from-equilibrium dynamics.

2.1.4. Cellular Automata

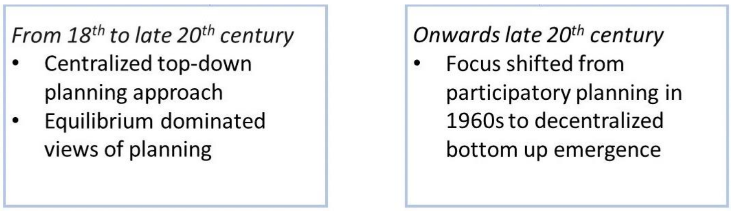
This is a model, spatially disaggregated and made on a two-dimensional lattice of cells, where land use is represented by each cell and processes of change are determined in the neighborhood of any local cell. The evolution and emergence of global patterns are observed through several discrete steps.

2.1.5. Agent-Based Models

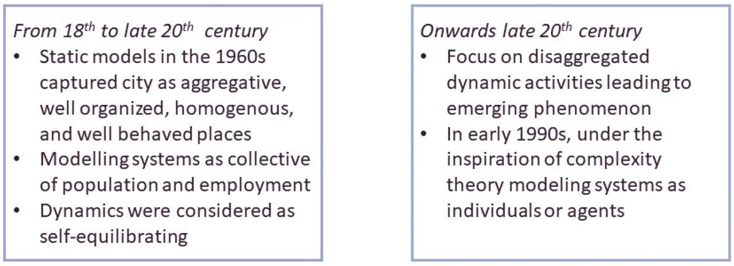
In the 1980s, this class of models was originated as the bottom-up approach. It presents the actions and interactions of adaptive agents as it is based on objects at the elemental level to reflect their behavior through time and space. Thus, the focus is on emergent spatial patterns from the very micro level through time.



(a) *Dynamism*: Static to Volatile System



(b) *Planning*: Top-down to Bottom-up



(c) *Modeling*: Macro-Statics to Micro-Dynamics

Figure 2. Main Features of The Timelines: Dynamism, Planning, and Modeling.

2.1.6. Network Analytics

One of the approaches to explain and examine complex systems is network analytics, which concentrates on associations between actors. Network science has been extensively used in urban studies and focused on the interactions between individuals and other systems. For example, Markus Schlaepfer's work built a generalizable model of place-visiting patterns and flows to depict the scale of needs and activities [6].

2.1.7. Models Inspired from Systems Perspective

Luis Bettencourt, a scientist at Los Alamos National Laboratory, and Geoffrey West, distinguished professor at the Santa Fe Institute, show emergence in cities and from a systems perspective quantitatively demonstrate how the whole is greater than the sum of its parts [30,31]. This approach views the city as an organism that grows in size, utilizes energy, and generates waste. In their work, as a result of the social interactions among agents, cities exhibit macroscopic superlinear scaling patterns in socioeconomic properties. Batty has highlighted the primary basis of complexity science on analyzing cities and demonstrated that cities are made up of flows of people, goods, services, and information in diverse cultural, physical, and digital networks [8].

According to the disaggregated level, cities are emergent consequences of interplays among adaptive agents. Individuals and organizations continually interact, contact barriers, arrive at decisions, and adapt accordingly. Agents perceive and respond to the environment and their fellows, thus being involved in feedback to policy interventions, which shape their perception of life. This acknowledgment of agents, as dynamic and adaptive, demands people-centric planning and the deliberation for adaptive capacity in policies. https://www.ura.gov.sg/Corporate/Resources/Ideas-and-Trends/Complexity-and-Urban-Dynamics (accessed date: 10 December 2021).

2.2. Functioning of Cities

The main urban theories that have dominated urban modeling are based on following types of equilibria [10]. The timeline of these theories is shown in Figure 3.

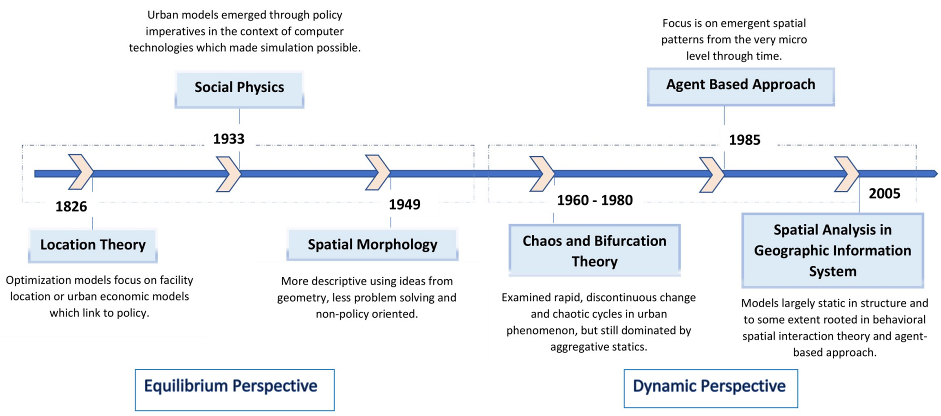


Figure 3. Timeline of the Salient Theories in Urban Modeling: From Predictions to Understanding and Innovation.

2.2.1. Cities in Disequilibrium

Michael Betty stated that it is likely that a system can be in equilibrium, out-of-equilibrium, in disequilibrium, and far-from-equilibrium all at the same time. Consequently, anything that diverges from the steady state can be called a disequilibrium [8,29]. Moreover, the equilibrium concept can vary dramatically conditioned upon its application. For example, in the City of London, where buildings are continuously being reconstructed, and where populations are perpetually varying dramatically in composition and type, the physical structure has remained moderately stable with respect to the street pattern. Batty considered a distinctive kind of equilibrium that is being sustained in the action for order facing chaos, concerning how cities utilize energy and bring innovations. This idea of a system that is far from equilibrium can be best understood in its physical form [29]. Unpacking the city dynamics reveals that the ideas of cities in equilibrium is a superficial perception, as equilibrium merely makes sense when we think of cities physically. Numerous countervailing forces that give rise to different temporal and spatial scales bring heterogeneous function and volatile urban form. Catastrophe and chaos theory help us understand the discontinuity and far-from-equilibrium urban structures [10]. In this regard, Batty concluded that city happenings are disconnected from the physical form of a city as seen in the contemporary world, there is no synchronization between what happens to the built environment in the city and fluctuations in human behaviors, activity, and patterns of movement [29].

2.2.2. Cities in Dynamic Equilibrium

Urban development can demonstrate counterintuitive dynamic behavior. This was emphatically demonstrated by Jay Forrester, the founder of the field of system dynamics. For instance, Forrester showed that low-cost housing and training programs for the under-employed can counterintuitively contribute to the degeneration of the urban environment. On the other hand, establishing job opportunities by replacing slum areas with industry can lead to desirable long-term trends. Forrester's model of urban dynamics shows that urban problems (housing shortages or unemployment) are the result of internal forces and cannot be resolved by undertaking external symptoms [32]. Any city development program affects the stability of the system as a whole, despite the potential of the individual program. Forrester also highlighted that striving to improve all aspects of the city will result in the inevitable problem of bringing more people than the accommodation capacity of the city [32]. He termed this the attractiveness principle. He proposed that urban planning should concentrate on balancing the positive and negative dimensions of urban life. Adjusting specific elements of a city's attractiveness while guaranteeing that the total attractiveness of the city remains the same can assist in achieving a city's development.

2.2.3. Cities in Adaptation

Cities stimulate social interactions and complex exchanges of people where feedback processes lead to counter behavior. There is a constant adaptation, not equilibrium, as Bettencourt and West present through the scientific understanding of dynamics, growth, and evolution of cities, predictably and quantitatively [30]. Their main findings are based on scaling laws such as the bigger the city, the more the average citizen owns and utilizes. On average, when city size systematically increases per capita, socio-economic measures such as wages, patents produced, gross domestic product, educational institutes increase by around 15% more than the expected linear growth. By the same token, traffic congestion, crime, and illnesses all increase, following the same 15% rule [31]. They show that as cities are robust, success, once accomplished, is sustained for decades, but the reverse can also be true [31]. Thus, policymakers should improve city performance corresponding to baselines for their size, determined by scaling laws.

2.3. Humanistic and Sociotechnical Aspects of Smart Cities

In many discussions related to smart cities, important considerations are altogether ignored such as the essence of social capital, or trust between individuals and communities, is rarely discussed. Too often, we are presented with a vision of a smart city as a mechanical system that fails to account for humanistic elements that bring color, noise, sights, and sounds to what would otherwise be a robotic, soulless structure. More crucially, the notion of inclusion seems to have been consigned to the margins; do we construct cities to accommodate individuals who can buy smartphones, tablets, and IoT-connected gadgets, or do we create cities for everyone? [21]. Previous research has shown that technology can be a double-edged sword and it can be used to facilitate human development or derail and impede it [33]. Luckily, with the rise in interest in human-centered artificial intelligence (AI), there is rising interest in development future human-centered smart cities [34,35] (some salient features and related aspects are depicted in Figure 4).

2.3.1. Development Challenges of Smart City

With the continuous growth of cities, their challenges require careful consideration. Although most of the global GDP is yielded in cities, not everything occurring in cities indicates praising externalities. In cities, inequalities, pollution, and crime rate are assertively present. If these problems are not significantly solved, the consequences will be dire [36]. Some salient challenges of smart cities are noted next.

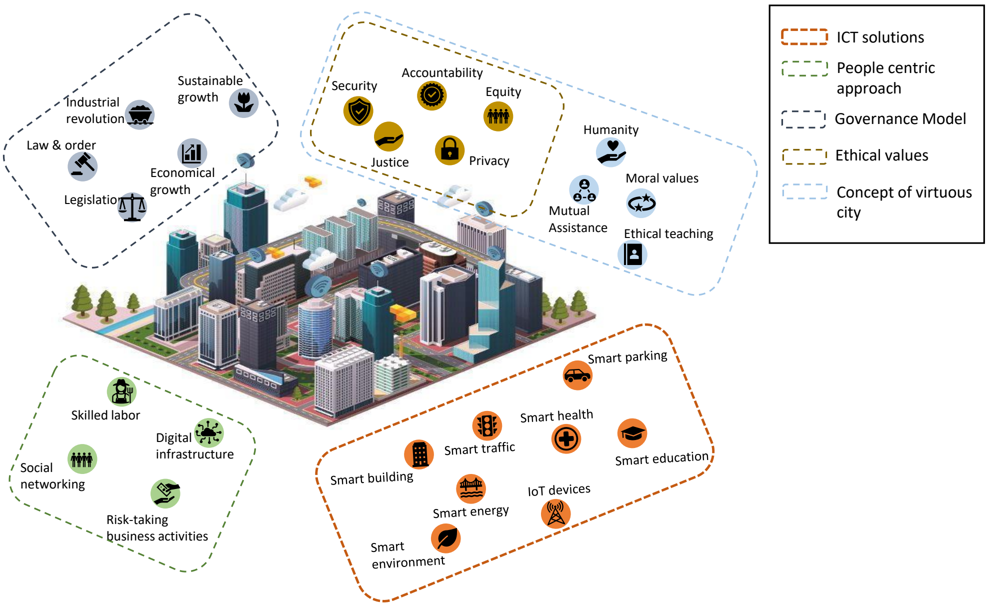


Figure 4. Holistic overview of a smart city highlighting that the concept of smart city is not limited to implementing ICT solutions. (Authors' own).

Lack of Governance Model

Smart cities are often termed digital or intelligent cities. Due to variations in defining a smart city, urban planners have developed many theoretical and technical policies. Unfortunately, despite various initiatives and the availability of advanced technology, not enough progress has been achieved in building smart cities. The major limitation in realizing the vision of smart cities is in the lack of focus on the multidimensional operating nature of cities. Regulation, planning, financing, and operating a city is a complex undertaking due to the involvement of multiple stakeholders with various dependencies and interdependencies [5]. The development of a model of government is one of the main challenges for applying smart governance in smart cities. Combining top-down policies with bottom-up endeavors is challenging for making governance models more flexible. Demographic transformations and territorial solidarity are also required to enhance the governance models.

Lack of Urbanization Model

The development of productive markets and industries is the main challenge for the smart economy. Rather than focusing only on one economic sector, designing a multisectoral economy will help to make cities resilient to crises. Proper research of conditions that causes the urban agglomeration and interconnections of their industries can also improve the resistance to economic downturns.

Scarcity of Resources

The availability of clean drinking water and hygienic food has become a major challenge for cities because of rapid climate changes. In the coming years, the shortage of water will increase, which can have adverse effects of agriculture production. Poor water supply and energy network conditions are the main reasons for the shortage of resources in cities. With the development of new supply networks, improving the efficiency of the existing supply structure is also required to minimize the discrimination in the distribution of basic resources.

Lack of Social Security

Interconnectivity of ICT devices enables multiple parties to access the information and data of citizens. Multiple stakeholders contributing to the development of smart cities use the data, so each person using the digital facilities is at risk of data manipulation. There exists a gap between the privacy standards due to the various priorities of each association. Smart cities must take into account privacy concerns while regulating the data.

Poverty and Inequality

Poverty and insecurity are major challenges causing the loss of capability to attract new businesses and talent. Instability of government, the violation of laws, corruption, and social polarization are also the main issues causing business downturns. Social and living conditions improvement is necessary for a promising bright future for the smart city.

Innovation Environment

Another difficulty is the creation of an innovation environment for the city, with a particular emphasis on Industry 4.0, as well as the attraction of talent and capital. A critical topic is how to build a smart, sustainable, and sharing community that can attract and keep creative minds, entrepreneurs, and innovators, while also reducing costs. A related difficulty is the provision of cheap housing to accommodate talent bases when real estate prices begin to rise as a result of the increased demand for a higher quality of life in urban areas [21].

Visionary Political Leadership

Considering problems that include bureaucratic misalignment, privacy issues, a lack of funds, and a lack of awareness about what is feasible, to succeed, visionary political leadership at all levels is essential. This leadership must have a comprehensive knowledge of the potential and the technical competence to assess the benefits and dangers. Most essentially, we want leaders who are capable of diagnosing the issue, comprehending the technology, and communicating both the costs and the advantages openly and honestly to their teams and stakeholders. They must also be prepared to deal with the political backlash from a segment of the public, if necessary.

2.3.2. Impact and Pitfalls of ICT-Focused Smart City Solutions

Algorithm design is not merely a technical task. The techniques used in ML algorithms are unable to question, and data is shaped by collection practices and incorporate current politics. For instance, police data include police activity and service requesting tendencies instead of crime. Therefore, given the fact that ML algorithms rely on historical data, we cannot trust predictive algorithms to make municipal decisions that have a huge impact on society's political outcomes as "more fundamental than biases within data are the politics embedded within the algorithms" [37]. Even though it appears that ML algorithms do not make assumptions about the world, data-driven algorithms often incorporate the priorities, beliefs, and choices of their creators. The decision to either focus on ignoring the false positive or false negative completely can make or break the model. For instance, the software of a self-driving Uber car, while prioritizing avoiding false positives, e.g., avoiding responding to hurdles such as plastic bags, killed a woman in Arizona in March 2018 [37]. Furthermore, outcomes of the ML models are based on characteristics fed in the model in determining past outcomes. The training data comprising historical data samples classified into categories form the basis of ML algorithms used in a smart city. The problem lies here as past outcomes do not always be neutral; data depicts the social contexts. The danger becomes more intense when governments use algorithmic decision making. As it gives significant power to the unaccountable system developers to dictate municipal priorities. Algorithmic decisions seem only a technical choice; but when data are influenced by developers in terms of choices, values, and judgments about what input factors from data are included, this vastly influences public policy.

2.3.3. Combination of Human, Social, Entrepreneurial, and Infrastructure Capital

Mansoor and Chandra have argued that the notion of a "smart city" should not be restricted to the deployment of just the most up-to-date technology to urban areas [21]. They have proposed that the components that make up a smart city are built on a promising combination of human capital (such as skilled labor force), infrastructural capital (such as high-tech communication facilities), social capital (such as trust and open network linkages), and entrepreneurial capital (such as creative and risk-taking business activities) that can be solidified over time [38]. This implies that the smart city idea is not confined to the distribution of ICT; rather, it is centered on the needs of the residents.

2.3.4. Humanistic Principles and Virtuous Cities

Solving the rising problems of urbanization with smart cities is by itself not adequate—humanistic principles should be at the core of all solutions. For theorizing about such humanistic principles, it serves us well to look at the philosophy of virtue and virtuous cities. Plato's 'The Republic' claims that the model of an ideal city provides happiness and the ultimate human perfection [39]. Al-Farabi's philosophy becomes very relevant for advancing democratic reforms and harmony in the city [40]. The study of the political philosophy of Al-Farabi, the medieval Muslim philosopher, especially his teachings on the need for mutual assistance between people, his focus on the intellectual and moral perfection of man and society, his social and ethical teachings, are central to the idea of a virtuous city. https://maypoleofwisdom.com/al-farabi-chasing-the-objectivity/(accessed date: 20 October 2021) The virtues highlighted by Al-Farabi have two dimensions: ethical and intellectual. For ethical virtues, he considered justice, generosity, temperance, and courage; whereas, for the intellectual, he stressed intelligence, wisdom, and wit. The basic principle of Al-Farabi's virtuous city is justice. The dominance of justice unites multifarious and heterogeneous elements of the city as a whole [41]. According to him, virtue is the best moral quality. The making of the smart city should reflect on the virtues to restore values among people that would be lost if the smart city only focuses on technological advancement in the city. Shannon Vallor in 'Technology and the Virtues' presents vast resources to embrace ethics in challenges and development practices of technology. She puts forward solutions such as "improved technomoral education", "cultivating technomoral humility" or cultivating "renewed technomoral courage" [42]. She lists twelve virtues relevant to the contemporary human condition with sociotechnical opacity: truthfulness, self-control, humbleness, fairness, courage, empathy, care, courtesy, flexibility, perspective, generosity, and technomoral wisdom. For each of these virtues, Vallor has strived to uncover common roots amongst the traditions of Aristotelian, Buddhist, and Confucian virtue ethics, and elucidate their relevance to emerging technologies [43].

2.4. Complexity Science and Complex Systems

There are a number of schools of thoughts related to complex systems or systems thinking. Some prominent schools include General Systems Theory, which developed from the ideas of Ludwig von Bertalanffy [44]. A number of systems-related theories were introduced in the field of biological sciences in the early twentieth century. After 1939, systems theory has also been widely adopted by thinkers in the field of ecology, social sciences, and business management [45] . Another school is that of Chaos Theory, which gives central importance to dynamics and feedback and the emergence of unpredictable phenomena from systems due to these effects [46]. The field of Cybernetics, established by Norbert Wiener, also utilizes the central concept of feedback in machines and organisms to analyze how systems behave and evolve [47]. The field of Systems Dynamics was invented by Jay Forrester in the 1950s at MIT, USA, and this field has widely contributed to the popularization of systems thinking through the publications of Jay Forrester [5,48,49] and Peter Senge [50]. Systems dynamics is especially popular and effective in the study of complex problems related to business dynamics [51] and social change [52].

A complex system contains various individual components or agents that manifest the collective behavior and characteristics of the system. Examples of complex systems include biological systems, the international trading system, economics, finance, and government structure of a country. Consider the example of a biological system—a human body. It is not simply the collection of cells, and each cell is not a simple collection of molecules. Similarly, the personality, character, and consciousness of every human is a result of complicated interactions between the neurons and synapses in the brain. It is not usually possible to predict or exhibit the behavior of complex systems using the properties of individual components as the behavior emerges without any central control by the infinite iteration of simple rules followed by constituent parts of the system [6] through various intertwined nonlinear feedback loops [5]. Individual constituents gather to develop emergent patterns, a process known as self-organization. The complex systems hold the property that the basic building elements of the system remain conserved when we scale up from small to large systems such as economies, cities, organisms, and other evolutionary processes. All the fundamental principles and building blocks remain approximately the same independent of the increasing size and complexity of the systems [1]. The major determining factors of a complex system are scale and size, which give rise to nonlinear evolving behavior. There are two types of scaling: superlinear scaling states that "the bigger you are, the more there is per capita" and sublinear scaling states that "the bigger you are, the less you need per capita" [6].

Complexity science deals with problems and systems with unpredictable emergent behavior and consisting of nonlinearly interconnected parts. Traditional science focuses on the simple "cause and effect" relationship to extract the laws for controlling, measuring, and replicating a system. On the other hand, according to Phelan, complexity science postulates simple causes for complex effects [53]. He has stated that the core assumption of complexity science is that complexity in the world is a result of simple rules. Complexity science is not a single or unique theory, but an accumulation of various theories and conceptual tools from different disciplines [7].

3. Smart Cities as Complex Systems

In this section, we discuss the systems of smart cities and their functioning using various underlying principles and laws. We explore archetypes that can help mitigate the risks leading to unforeseen consequences, and also explore the views which differentiate smart cities from traditional ones. We discuss the need for causal modeling of smart cities that can nullify their inefficiencies, and discuss the models and theories used in literature for modeling the smart cities in detail. We end this section with a discussion on system-based challenges of smart cities.

3.1. System of Smart Cities

In the 1950s, with the application of general system theory and cybernetics in social sciences, scholars formally considered cities as a system. The basic idea behind this consideration is the concepts of controllers and feedback loops to steer the system towards achieving desired goals. However, this consideration required more significant interventions than anything that had been presented before in the field of urban planning [9]. Later on, the development of system theories in various disciplines supported the idea of treating cities as systems. For example, the evolution of spatial analysis in quantitative geography is linked with regional science representing the synthesis of urban and regional economics. The ideas of gravitational and potential energies from physics were used in transport modeling [45]. Analogies from sociology and political science were also chosen as the basis for creating management and control policies of cities [54].

In city systems, distance is a fundamental organizing concept, as seen in the various generation of urban distributions. Distance is a property of nearness to the most accessible regions and locations. The more accessible or attractive the location offers the lowest travel costs and distance to other places. In this scenario, travel cost or distance acts as an inferior good as the aim is to reduce the cost that occurred in overcoming it. The spatial competition also intimates that the number of sites, with the greatest accessibilities, is negligible compared to the majority of sites. The population density model implies that if in a circular city the most accessible place is the center, then assuming every place is of similar size, the accessibility decreases as the number of places by accessibility advances.

Various systemic principles are used to describe the functioning of smart cities as SoS. These are elucidated below [10].

3.1.1. Pattern vs. Process

A set of elements and their interactions through linkages due to economic and functional activities give rise to a pattern at a point in time. Tradeoffs between diseconomies and agglomeration economies cause patterns of activity to rise which emerge from the spatial choice processes of individuals and groups regarding location, activities in land use, and density profiles.

3.1.2. Evolution vs. Emergence

The interactions of inhabitants of the city result in collective behavior that is different from the properties of the components of the interacting inhabitants. Thus, this collective behavior is difficult to predict. For instance, the distance of work to and from home, travel cost and experience, and other factors cannot be sufficient to explain the patterns of people commuting in a city. Patterns, which are the product of many bottom-up individual decisions, evolve through time and give rise to surprising emergent behavior at any cross-section [10]. Three conditions are required for emergence in a system: high connectivity, a mechanism that produces new connections, and an adequately low level of control, since less control signifies more emergence and vice versa [55].

3.1.3. Scaling Laws

Network structures express the sprawl and compaction of city development; moreover, they provide scaling effects that define cities. As the elements and the whole of the city change, the size and shape of the entire city system change. Scaling ties together all processes and forms. For instance, according to the space, if an object scales, it shows the same proportions of its spatial form either as a smaller or larger object. It is more likely that the proportions of the object become distorted as changes in size also lead to an adjustment in proportions. For example, it is highly unlikely that a small town has a well-developed underground railway system because it requires many stopping distances which is physically impossible. On the other hand, other means of transport, such as trams, scale according to the small town [10].

3.1.4. Far-from-Equilibrium

Cities are far-from-equilibrium and sustained through a force of multiple countervailing drives that break down and create many different temporal and spatial scales, thus all combining in strong heterogeneity and volatility in the urban form [29]. Ideas about innovation and technological change modify city dynamics. Betty has concluded that city happenings are increasingly separated from their physical form and changes to the built environment are ever out-of-sync with transformations in human behaviors, patterns of movement, and globalization.

3.2. Use of System Archetypes in Smart City Modeling

Over the years, systems thinkers have cataloged a library of systems archetypes. They are useful to analyze patterns of behavior or misbehavior that arise in a different system and can help forecast unintended consequences [56]. Thus, a nuanced understanding of the root causes of system misbehavior, problem symptoms, and the reasons which are preventing them to move towards fundamental solutions can help in resolving the problems of smart cities.

Unintended consequences and underlying structure of smart city present how ML algorithms that seem only a technical task if deployed without any transparency and ethics embedded in the solutions can lead to biased and unjust outcomes such as incorrectly accusing persons as criminals, invading private information, increasing digital divide, and shifting growth funding from meaningful policy reforms to quick fixes, for instance, predictive policing that exacerbate the problem in the long run. Below, we have identified some of the common system archetypes in a smart city, also illustrated in Table 2.

Table 2. Summary of system archetypes described in paper for analyzing solutions of smart city problems.

Archetype Name	Description	Example
Fixes That Fail	An immediate fix leads to unintended consequences in the long-run [56]	Predictive policing that intends to reduce crime accentuates crime in the long run
Success to the Successful	Situation gets better for winners get better and worse for losers [56]	Based on a short-term success rate, resources are devoted to predictive policing at the expense of reforms for institutions
Eroding Goals	Deterioration of long-term goals at the expense of short-term fixes [56]	Monetizing incentives for sharing user data erodes privacy laws in the system
Shifting the Burden	Alleviation of problems with symptomatic solutions [56]	Reliance on technology undermines fundamental solutions incorporating virtues

3.2.1. Fixes That Fail

This archetype hypothesizes that a quick fix leads to unintended consequences in the long run [56]. It is depicted by two feedback loops that connect action and a result, with outcomes feeding back again in a circular loop. Reinforcing loop (R1) amplifies change, and balancing loop (B1) stabilizes change within the system. The causal links between the elements are presented with the associated polarity. Polarity can either be the same (represented by +) which depicts that the two elements move in the same direction or opposite (represented by −) which shows that the two elements move in opposite directions. As shown in Figure 5, a quick fix of using predictive policing for crime detection decreases the rate of crime. However, in the long run, an immediate fix leads to accentuating crime in the society when predictive policing fails to detect the actual crime and penalizes innocent people only because trends from past data predict such outcomes.

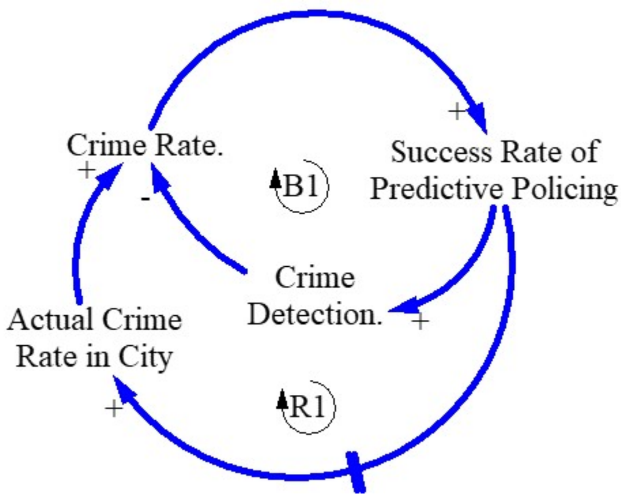


Figure 5. Fixes That Fail: Predictive Policing that Intends to Reduce Crime Accentuates Crime in the Long Run.

For instance, St. George's had unfairly rejected hundreds of applicants from minorities and women despite exceptional academic credentials. When the algorithm drew on its training data of previous decisions of admission, it deduced that St. George's considered women and minorities to be incapable. Instead of learning to identify the most academically qualified candidates, the algorithm learned to identify the applicants that looked the most like those the school had admitted in the past [37]. Similarly, decisions in smart cities solely based on predictive policing algorithms that rely on historical data may punish the honest and result in zero accountability for wrong-doers, thus increasing crime in the city.

Politics within Algorithms: In addition, data collection can be biased because data are collected that fir the social bounds and are shaped by reporting and collection practice, thus, politics is embedded within algorithms. Furthermore, reform is not only required in making predictions unbiased, but also in tackling the biased prediction issue of predictive policing regarding policing methods as accurately based on facts. However, facts, i.e., crime statistics are termed as "poor measures of true levels of crime", according to criminologist Carl Klockars. Thus, those statistics are not the depiction of the actual levels of crime across society as what police termed as crime are a depiction of the policy priorities and activities [57].

The current solutions are adapting social theories to justify ML models, as even the models are not capturing the complex interconnections of society, but rather they "reflect the priorities of existing institutions and power structures." With regards to the police departments and courts, according to Ben Green, an affiliate at the Berkman Klein Center for Internet and Society at Harvard, who studies the social and political impacts of government algorithms, "When deployed within this framework, ML will be an ineffectual (at best) or counterproductive (at worst) tool for social justice" [37]. Instead of using ML to improve city functioning such as predictive policing by perceiving it as a value-neutral approach, there is a need to evaluate whether the police practices are addressing social disorder and are an effective tool for social justice.

Moreover, smart cities may also unintentionally increase an existing divide between already digitally marginalized and better-connected groups. Smartphone applications that can provide a platform for citizens to report their problems seem a perfect solution towards resolving the street problems; however, it is a quick and wrong fix, smartphones are mostly owned by wealthier residents or those with the knowledge on how to use those smart applications, hence, actual problems remain unaddressed [58].

3.2.2. Success to the Successful

This archetype states if one group is allocated with more resources than another equally capable group, the resource-sufficient group succeed and justify the case to gain even more resources, which creates a widening gap of performance between two groups and unfair disadvantage to the losers [56]. Reinforcing loops (R2, R3) in Figure 6 illustrate the case when based on short term success of predictive policing, resources are devoted to policing departments without foreseeing the long-term consequences of depriving resources for other departments.

As smart cities facilitate police, welfare offices, employers, and others with data, it causes surveillance of the urban poor. Reinforcing loops (R2 and R3) present as more resources devoted to police for predictive policing lead to the success of predictive policing, and thus crime detection; however, at the expense of devoting resources to other departments such as welfare working for the provision of electric benefit transfer cards to mothers. For instance, a single mother loses welfare benefits after an algorithm flagged her with the camera footage identification at a protest [37].

Quick Fixes at the Expense of Meaningful Reforms. Similarly, R2 and R3 show growth funding to police after its immediate success depriving institutions of the resources necessary for meaningful reforms and institutions. Unlike those who leap at the quick-fix solution promised by predictive policing, Robert Sullivan, criminal justice coordinator, emphasizes that improving the criminal justice demands a step-by-step process over the years [37]. According to Alex Vitale, "Police function as a tool for managing deeply entrenched inequalities in a way that systematically produces injustices for the poor, socially marginal, and nonwhite" [59].

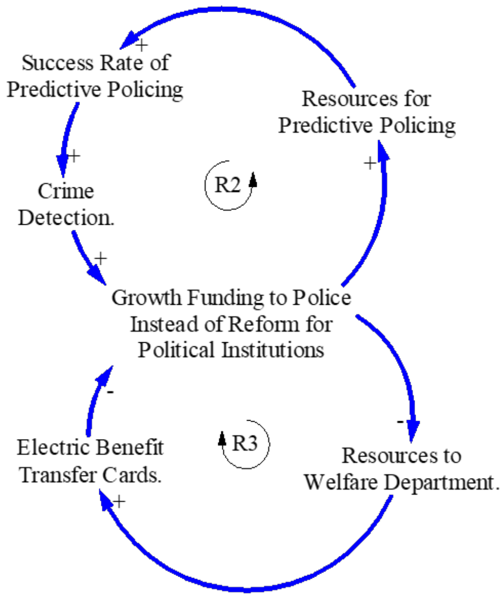


Figure 6. Success to the Successful: Based on a Short-term Success Rate, Resources are Devoted for Predictive Policing at the Expense of Reforms for Institutions.

3.2.3. Eroding Goals

This archetype presents a gap between actual performance and stated goals. It examines the state of the system when the goal is comprised to close that gap, which eventually leads to deteriorating the actual problem [56]. The balancing loops B2 and B3 in Figure 7 present how a system in built structure erodes the goal itself. Privacy laws that intend to protect the privacy of users lower the gap between the stated goal of privacy protection and the actual goal achieved as monetizing incentives for sharing detailed data create pressure to adjust the goal of privacy. The incentive structure within the system that promotes the sharing of user data hinders the implementation process of privacy laws.

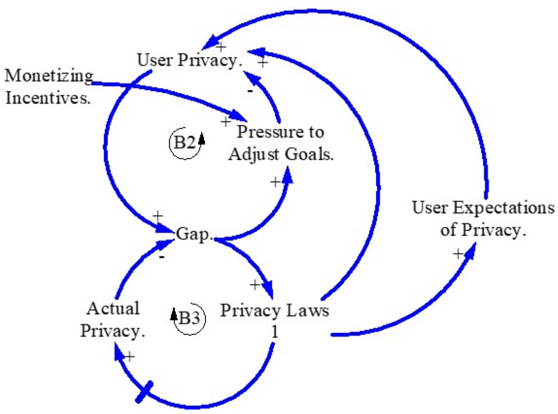


Figure 7. Eroding Goals: Monetizing Incentives for Sharing User Data Erodes Structure of Privacy Laws in the System.

Incentive Structure Invading Public Privacy. More danger arises when implicit information is disclosed from data combined with AI such as with the information where the user has been tracked. The monetizing incentives further motivate to reveal the maximum information about users. ML algorithms can predict user preferences about visiting in terms of places they will visit next and with whom. The risk is not merely that one's identity can be revealed from apparently anonymous data; when data are combined with AI, there is a potential to infer a significant deal of personal information that is not explicitly included in a dataset [37]. With detailed information about where one has been, ML algorithms can predict the behavior of that user, a location where one will be and with whom. Moreover, the photos or other benign data shared on Facebook or Instagram algorithm can predict the feeling of the person, political or religious affiliation, and even marital status. This behavioral identification by algorithms presents a grave picture of the invasion of public privacy and monetizing incentives aggravate the situation.

3.2.4. Shifting the Burden

This archetype hypothesizes that because of reliance on symptomatic solutions problem symptom persists and invariably happens. Solutions that should be seen as a one-time fix create side effects that reduce the urge for fundamental solutions, thus aggravating the problem [56].

Technological Solutions Undermining Human Values. As depicted in Figure 8, to solve the rising problems of cities such as governance and regulation, technological solutions are perceived as forward-looking. However, sole reliance on technology not only creates side effects such as loss of community, loss of traditions, and loss of ethical values, as shown in reinforcing loop R1 in Figure 8, but it also worsens the existing environmental and social challenges. Thereby, we cannot shift the burden to science and technology without incorporating human values and ideals about the virtues.

Peter Senge in Presence elucidated this phenomenon as, over the past two hundred years, rising dependence of Western culture on reductionistic science and technology are diminishing wisdom. Technological powers are failing to integrate physical, emotional, mental, and spiritual aspects of growth and human development [60].

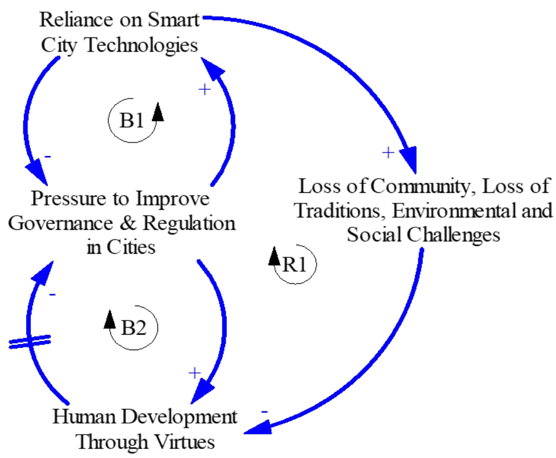


Figure 8. Shifting the Burden: Dependence on Technological Solutions Undermines Fundamental Solutions Regarding Capacity to be Human Through Virtues, Adapted from [60].

3.3. Systems Theory on Smart City

According to the systems theory, a smart city is an environment comprising particular systems which are further divided into subsystems. The interconnection or interaction of subsystems within the smart city indicates energy, information, or control relationships among subsystems. The main difference between traditional cities and smart cities lies in the fact that contrary to the traditional city in which systems interact only with the environment, systems in smart cities are interoperable with other systems and interconnected by information relations, thus, information management becomes more crucial [61].

3.3.1. Smart City as Cyber-Physical System

According to one of the subsets of systems theory, a smart city can be viewed as a cyber-physical system (CPS), the virtual world of the smart city is interconnected with the physical part composed of a network of sensors in intersection with wireless devices with Internet and cloud service [62]. The flow of information through CPS consists of traffic conditions, air quality, parking spaces, vehicles, roads or buildings, or healthcare. On the other hand, the collection and dissemination of data can also be harmful [63]. For instance, when smart parking solutions inform drivers about the available parking spaces, this leads to traffic congestion where few parking spaces are available.

3.3.2. Smart City as Multi-Agent System

As human behavior is difficult to predict, systems within cities are dynamic and nonlinear. Heuristic models are used to model complex systems. As systems theory classifies smart cities specifically as CPS, they can be modeled by tools, such as system dynamics or Multi-Agent Systems (MAS). MAS can model every object (car, building, signal, etc.) as an agent, which acts based on a decision considered under its location and perception of the environment [64].

3.4. Causal Modeling of a Smart City

For the past few years, the concept of smart cities has revolved around the implementation of advanced technology. It is a general thought that we require an abundant amount of data and sophisticated models to build a smart city. These models require theories of human behavior to support them. However, in the recent pandemic, it has become evident that cities are not as smart or resilient as we believed. Against expectations, smart cities have fallen in various ways, but the underlying causes and facts are not straightforward. For example, according to Braess's paradox, the efficiency of the transport network or electric grid can sometimes be decreased by constructing a new road or by adding a new link [65]. It may appear counterintuitive, but many real-world examples of this phenomenon exist. Therefore, rather than applying oversimplified and shortsighted solutions, we require analysis for revealing the hidden causes and their correlation with effects.

The core idea underlying Dynamic Causal Modeling (DCM) is that brain networks are an input–state–output system in which unobservable neural dynamics govern causal connections. These "hidden" interactions are characterized by coupling parameters, which represent effective connectivity and are referred to as a causal model [66]. Generative models, i.e., agent-based models or dynamic causal modeling, can help in detecting causal relations in the data. This lessens the risk of policies or decisions going wrong. Chang et al. applied the agent-based model to compare various intervention techniques, including a ban on international air travel, patient isolation, home quarantine, social distancing with varying levels of compliance, and school closures. They found that the intervention of closing schools is not effective for assertive benefits unless associated with a high level of social distancing compliance [67]. Nunes et al. applied a system dynamics approach to identify the factors that assist in the success of a smart city. They also identified the cause-and-effect relationships among the determinants that facilitate the designing of smart cities [68].

Control Theory: Smart City applications, in general, raise concerns about promoting behavioual change to make better use of existing resources, as we struggle to manage traffic, pollution, and food production with ever-increasing demands on natural resources. The optimum management of resources is a classical concern of control theory. In order to allow for better and quicker operational choices, real-time control systems provide data to dashboards and enterprise resource planning, asset management, and reporting systems.

Models in the field of Smart Cities, on the other hand, cannot be easily generated from first principles and must instead be empirical, that is, based on data gathered from measurements of established procedures. Furthermore, the empirical data can only be gathered from the system as is, not from controlled tests over a variety of operating points.

An attempt to enhance the processes in question, such as by providing information to the agents involved, establishes a previously unnoticed feedback loop. This change in the underlying process may invalidate the empirical model; there were simply no data available at the time of the model's development to capture the dynamic influence of such a feedback [69]. Frequently, offered solutions fail to account for this feedback cycle. This necessitates a considerably more extensive investigation of prediction and optimization under feedback than has hitherto been done. The impact of transportation delays, as well as the fact that all agents are instantly notified of signals, adds to the complexity of the situation [70]. The necessity to construct models of large-scale systems that can be fed back is a major roadblock to employing various control techniques in Smart City applications. In dealing with such consequences, Smart City research have a lot to learn from both ecological and control theory.

3.5. Application of Theories and Models in Smart City

This section sheds light on the application of models and theories in smart city and Table 3 summarizes the advantages and disadvantages of these theories and models.

Table 3. Advantages and disadvantages of theories and models used in modeling a smart city.

Method	Description	Advantages	Disadvantages/Limitations
Social Network Analysis	Investigation of social structure in terms of nodes, edges, or links to connect them	• Can generate an understanding of socio-institutional structures, actors and linkages, and ways to improve information and knowledge transfer • Can provide information on decision framing and key actors. • Can provide quantitative information and correlations to understand network variables • Quick and relatively easy to conduct and encourages participation across diverse viewpoints and actors	• Subjective bias and can be difficult to generalize. • Time-consuming and intensive process • Does not have a temporal or spatial dimension. • Networks have artificial boundaries (often necessarily). • Design of process is critical to obtain as many differing viewpoints as possible.
Agent Modeling	Focuses on emergent spatial patterns from the very micro level through time.	• Able to model heterogeneous populations in which statistical properties of distribution are same in various parts of distribution • Allows for discrete models rather than continuous • The researcher does not need to have an understanding of the aggregate or big picture behavior of the phenomenon	• Not able to deal with homogeneous data • Can be computationally expensive
Decision Making Methods	Produces an efficient methodology for optimizing complex decision-making processes throughout all stages.	• Improve the degree of acceptance of a solution and commitment • Allow the citizens to participate in taking decisions as the data of citizens is used in making decisions • Provide well-informed reforms in city if decisions are based on extensive data sets	• Can be time-consuming • Computationally expensive • Can be biased
Spatio-Temporal Network Data Analytics	Network semantics are generated from location-aware sensors in urban transportation networks.	• Find useful characteristics of data from the dynamic interplay between space and time • Provide analytics that describe patterns in data based on time.	• Continuous and discrete changes of spatial and non-spatial properties of spatiotemporal objects makes the data complex to handle • Correlation of spatial data and temporal data must be take into account for analysis
Multiscale Modeling	Uses multiple models at micro, meso, and macro levels to understand a complex adaptive system.	• Allow the different scaling for multiple phenomenon interacting with each other • It allows the prediction of system behavior based on knowledge of the process–structure–property relationships.	• Measurement of scaling parameter could be challenging • Minor error in selection of scaling parameter can discard the useful information and highlight pointless information

3.5.1. Social Network Analysis

The concept of the Spanish Network of Smart Cities allows the investigation of hierarchy connections and centrality among cities and corporations that implement strategies of a smart city. These strategies assembled on a two-way network of companies and cities with the measures of correspondence and betweenness, Gini index, and inequality for each of them. Findings suggest these networks become a nationwide gateway for multinational companies to expand in national markets of cities [71].

Radulescu et al. have used a holistic sustainability-focused Complex Adaptive System lens for understanding the complex dynamics of smart cities. Social Network Analysis (SNA) served as a tool for mapping the knowledge flow between different knowledge-based organizations to the meso- and micro-economic levels within a considered area, which was particularly helpful in identifying the major influential elements in a collaborative model of a smart city. SNA also contributes to defining the key competencies and the skilled development of human resources in the innovation network that is a base for the collaborative model of a smart city [72].

3.5.2. Agent Modeling and Network Analysis

With the help of spatial syntax tools and graph theory, the topological street network aspects of Cartagena de Indias are examined. Street congestion is analyzed using a simple agent-based model considering the traffic knowledge of the agent. It is essential to recognize the decision-making capability of the agents in the system to define the emergence of traffic congestion as the topological properties of the network are the partial cause of localized congestion [73].

3.5.3. Street Network Models

Graphs are the most common street network mathematical models that represent both the topology and geometry of street networks as a depiction of the real world. A set of nodes that are elements N in the graph is linked to one another by a set of edges that are connections E. Either node can be connected to a different node or to itself in set E through edges. Multiple edges as parallel edges can also connect the same nodes [74].

The street network primal graph represents junctions and dead-ends as nodes and connects street segments as edges, which is the opposite of a dual graph of a street network that models intersections as edges and street segments as nodes [75,76]. Real-world street networks have parallel edges, self-loops, restrictions of flow directionality in terms of one-way streets, and nonplanar elements in the form of overpasses and underpasses [74].

3.5.4. Multi-Agent Autonomous Intersection Management (MA-AIM) System

Vehicles leveraging both Edges of Things (EoT) and Blockchain facilities can be managed safely by Multi-Agent AIM (MA-AIM) system based on Vehicle-to-Infrastructure (V2I) and Infrastructure-to-Vehicle (I2V) communications. The proposed system includes an Intersection Manager Agent (IMA) that communicates with vehicles via driver agents that are installed on them in an EoT environment. IMA uses Blockchain mechanisms to coordinate the intersection of vehicles. It is an essential component for the management of road intersections and can govern the safe intersection of vehicles via bidirectional communication with them [77].

3.5.5. Decision-Making Methods

Decision-making methods are categorized into AI, multi-criteria decision making, integrated methods, and mathematical programming [78,79]. Multi-criteria decision making (MCDM) is used for every decision in all phases of smart city projects. Whereas, MP and AI methods are commonly used for making functional and tactical decisions. The dearth of decision-making tools in developing cities elevates the negotiation between various stakeholders [79].

Mathematical programming (MP) methods optimize objectives by estimating the constraints for helping stakeholders to make effectual decisions. For this, various optimization methods, such as goal programming, stochastic programming, linear programming, and data envelopment analysis, have been used. Advanced techniques have been introduced in MP methods to reduce the limitations related to nonlinear properties and dynamic complexity. There is also the integrated methods methodology which aims to integrate the benefits of the afore-described methods [80].

3.5.6. Spatio-Temporal Network Data Analytics

Spatio-temporal network semantics are generated from location-aware sensors in urban transportation networks such as temporally detailed roadmaps, traffic signal timings, GPS tracks, and vehicle measurements collectively call Big Spatio-Temporal Network (BSTN) Data [81]. BSTN has value addition potential for various smart-city use-cases including navigation services that recommend eco-friendly routes. However, BSTN data put forth notable computational challenges concerning the current state-of-the-art analytic techniques used in these services [82].

3.5.7. Cognitive Work Analysis by Human Factors and Ergonomics Approach

Stevens et al. have used a novel approach to model smart cities as complex systems. Drawing from the discipline of Human Factors and Ergonomics (HFE) of Cognitive Work Analysis, a Sociotechnical Systems (STS) is applied to assist in the designing, modeling, and evaluating of the complex system of the city within which cities are STS (humans, technology and their environment). Human operators are fundamental elements, but they interact with many technical components (e.g., nuclear power plants). The smart city was modeled according to five hierarchical levels—documenting, defining, and connecting the objectives, values, priorities, performed activities, and physical objects. HFE, specifically the STS approach, aims to jointly optimize the socio (society and people) and technological (non-human) aspects of the surroundings [83].

3.5.8. Multiscale Modeling

Multiscale Modeling (MM) is a kind of modeling that at different scales of resolution simultaneously uses multiple models at micro, meso, and macro levels to understand a complex adaptive system at each level. It helps decision makers in reviewing and monitoring the model from different perspectives at a particular level without interrupting other levels. In mega cities and smart cities, it paves the path for multiple emerging intelligent applications aiming to acquire decreased computational complexity and cost, sustainability, reliability, efficiency, and much more in smart city subsystems, including smart transportation, smart healthcare, smart community, smart economy, and smart industry [84].

3.6. Smart City as Systems-of-Sub-Systems

The smart city consists of systems involved in integrated and interrelated relationships within and outside systems leading to the smart city comprising complex systems-of-subsystems (SoS), a set of heterogeneous independent systems collaborating to achieve their purpose [85]. In European cities such as Manchester, Amsterdam, and Stockholm smart city implementation has incorporated a decentralized bottom-up approach. Smart cities constituents are deployed in fragmentation, each focusing on its objective; thus, they are a missing collaboration that leads to unsustainable solutions [58]. Systems perspective accounts for the varying balancing and reinforcing actions of different stakeholders (individuals, organizations, local or government authorities, etc.) Furthermore, we have to be mindful that cities are not only composed of material construction, but also legacies of cultures and ways of life.

An example of how multiple independent systems can integrate towards SoS can be understood through flood detection in an urban agglomeration as shown in Figure 9. Monitoring and emergency system collect information from multiple systems aiming towards effective monitoring with the support of authorities to reduce flood impacts. The river water level is assessed through a network of sensors in the river monitoring system, which indicates the risk of flood. Meteorological systems, in turn, monitor atmospheric parameters using employed weather satellites in the system. Drones and digital cameras in a surveillance system estimate the flow rate of the river to improve the accuracy of the measures captured by sensor nodes of the monitored river area. Then, multimedia data are combined with river monitoring and meteorological systems for flood detection. Moreover, an emergency can trigger firefighters, police, traffic management ambulances, or other city services [1,85]. Hence, by analyzing the extent of flood damage with different collaborating systems, the system optimizes and addresses the emergency with the best resource allocation.

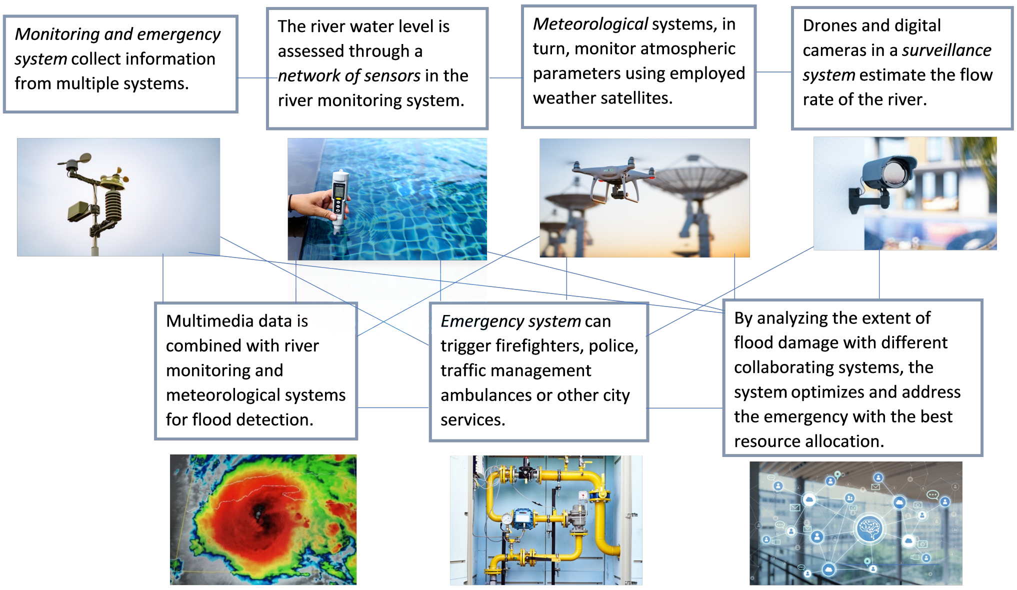


Figure 9. Smart City as a Complex Systems-of-Sub-Systems (SoS): A set of heterogeneous independent systems collaborating to achieve their purpose. It consists of systems involved in integrated and interrelated relationships within and outside systems.

A smart city as a complex system allows us to holistically view the different projects. It gives numerous agencies working under varying domains to interact, share, use information across domains, and thus coordinate actions. These systems integrating synergistically are characterized by their functions such as 'sensing, information management, analytic and modeling, and influencing outcomes'. Hence, with a holistic view of the city, the urban planner can better extract information regarding environmental variables and human behavior for the best allocation of resources (water, land, transportation, etc.) At the managerial level, actors can view planned interventions of cross-agencies. For example, during a crisis situation because of any natural disaster, all actors with coordinated effort can better decide where to allocate available resources [1]. Moreover, Naphade et al. have mentioned that planning, operations, and management are the three main processes that benefit from an integrated approach of systems at any cost [85].

3.7. System Based Challenges

In smart cities, systems are developing, managing, and evolving independently. Analyzing smart cities as SoS requires understanding the interactions among constituent systems which raises major challenges of design, engineering, and operation [86]. Following are some of the main challenges of smart cities when viewed through the perspective of systems.

3.7.1. Cognitive Challenges

Humans have innate cognitive limitations in processing information. The main challenge of applying complexity science to urban systems is that the emerging behavior of individuals who are themselves complex systems makes a city a complex system. This complexity at the multiscale level feeds into the individuals as cognitive constructs [87]. This is common to all social phenomena at a large scale, from states to markets to online communities. The city is the most fundamental and sensitive to all other social phenomena as it encompasses most human experiences in the socio-spatial context. Then, the capacity of the city functioning as a complex system also relies on how the cognitive representations of the city, elucidated by its inhabitants, affect their behaviors and choices and how, in turn, images at the macroscale into behavioral and spatial patterns.

3.7.2. Testing and Validation

Due to the complexity and unintended consequences in SoS, testing and validation are essential activities. Element- and service-level testing and validation are integrated activities that are anticipated at SoS and subsystem level to fix the spontaneous behavior. In the wider context and scope of SoS, it is difficult and costly to experiment for every modification in the subsystem, local changes to the subsystems may have surged overall SoS functionality [88].

3.7.3. Heterogeneity

The smart city relies on service delivery consisting of preexisting systems leading to a city-wide SoS. The engineering of this type of system has to encounter high heterogeneity of its elements and constituent systems. The elements which are distributed, autonomous, designed with distinct technologies and data formats, and possessed by distinct institutions, organizations, and agencies within the city become challenging to model.

3.7.4. A Multitude of Stakeholders

Enabling stakeholders for well-informed decisions is vital for sustainable planning to keep up with rapid urbanizations [89]. Single systems consist of predefined stakeholders involved with the system underneath production. SoS environments encompass a wider range of stakeholders from the particular constituent systems to the broad SoS [86]. Other than the technical and scalability aspects in the implementation of smart city systems as SoS, important matters related to visioning, strategy, approach, operations, sustainability, IT procedures influenced by stakeholders are more significant challenges in the more comprehensive horizon of smart city SoS.

4. Potential Pitfalls of Systems Model

The drawbacks limiting the application of systems model have been discussed which include limitations in accessing data and increasing computational costs, and finding a trade-off between protecting privacy and performing precise analysis.

The paucity of adequate data, stakeholders' reservations in presenting the causal relationships, and other important aspects of people, environment, governance, and living conditions, limit any systems model. Some of the main limitations are described below.

4.1. Computationally Difficulty Modeling

Understanding smart cities as complex SoS with the utilization of various above-mentioned models also poses numerous limitations in terms of the computation of social systems. A significant problem with mathematical programming methods is that they are too complicated for practical use by non-expert stakeholders [79]. In developing a transport model for the Tokyo metropolitan area at a micro-district scale, researchers put forth that an agent-based land use–transportation model is computationally difficult and quite data-demanding [73]. Similarly, data access and computational limitations are the main causes of the lesser knowability of comparative street networks worldwide at the urban scale [74].

4.2. Data Unavailability of Smart City Systems

The theoretical understanding and applicability in real urban settings become difficult with the sole focus on nodes and edges [81] in a system. One significant limitation of numerous studies on smart mobility aspects is the extensive dependence on simulations rather than live data from users of smart city services. In the analysis of consideration of the street as bidirectional, control elements such as traffic lights and the flow capacity of the roads were disregarded. The most significant simplification is the steady rate of agent creation per time step into the network, which is inconsistent with the dynamic human activity that possesses peak hours of vehicular movement. The studies also do not consider the variability of the dynamics of different vehicles. To incorporate such variables, it would be necessary to gather the real vehicular flow data according to the typology, but such data are not publicly available in the city [90].

4.3. Precise Analysis vs. Privacy Protection within Sub-Systems of Smart City

Spatiotemporal data mining for smart cities has side effects in terms of privacy. Privacy-preserving STDM concentrates on personal data privacy and corporate privacy. There are different approaches to protecting data privacy, such as suppression of the unique identities of individuals, perturbation via adding noise or randomizing the actual data, data sanitization, i.e., adding fake records. For the sake of data protection, these methods swap, delete, or modify some aspects. In this regard, researchers encounter a double-edged dilemma, i.e., performing precise analysis vs. privacy protection [91]. Moreover, a lack of specific knowledge of organizational behavior and network dynamics leads to uninterpretable analytical values concerning distinct periods of analysis. Thus, the predictions of organizational changes are low [74] and the system models cannot perform precise analysis.

5. Future Research Directions

A smart city can be defined not by its degree of adaptability to the most cutting-edge technologies currently available on the planet; rather, it is defined by the ability of urban inhabitants—whether they are leaders or members of their communities, or even both—to use ingenious solutions to solve lingering problems In this section, we discussed some open-ended research problems of smart cities.

5.1. Complexity Science for Digital Twins of Smart Cities

The proposition of Local Digital Twins is a term introduced by the European Commission. With AI and ML algorithms, it virtually represents a city and encompasses real-time and historical data of the city's processes. Creating exact digital copies of the world maintain biases if merely focusing on a data-driven perspective [1]. As societies are not automated machines, we cannot operate them like mechanical machines if we want to make cities more equitable, inclusive, and sustainable. There is a need to combine complexity science perspectives in digital-twins-like instruments to make the models adaptive and resilient that capture collective behavior and cater to causal linkages of intended and unintended side effects to human rights.

For a collective change in behavior in civil society, we need transformative changes extending from innovative ICTs that can transform future city services (transport, public safety, disaster management, public health, mobility practices, etc.) ICT ecosystem transformation and development processes complexity must be precisely known for influencing such innovations towards longer-term sustainability and inclusion of societal goals [89,92].

5.2. Ethical Implications of Smart City Systems

Ziosi et al. have outlined the analysis of ethical concerns of a smart city in four dimensions. These are: (1) network infrastructure, with the affiliated concerns of surveillance, control, security, ownership, and data privacy; (2) post-political governance, manifested in the decision making tussle between public and private and cities as post-political entities; (3) social inclusion, represented in the factors of citizen inclusion, and discrimination and inequality; and (4) sustainability, with a distinct focus on the environmental protection as a strategic element for the future [93].

A central ethical implication involves the surveillance of citizens. Surveillance is often closely concerned with the optimization of urban services and, more often, with increased security. However, it can easily be manipulated to control the behavior of citizens in remarkable detail. For instance, in San Diego, 'smart streetlight' cameras were originally introduced to allow city officials to examine traffic patterns, but were subsequently regularly employed by police officers to inspect purported crimes. https://www.bloomberg.com/news/articles/2020-08-06/a-surveillance-standoff-over-smart-streetlights(accessed date:

3 February 2022) This way, smart cities may advance the risk of becoming a catalyst for unnecessary surveillance, as well as at the cost of increased security deepening existing inequities and bias in systems.

Cities and employers at the expense of surveillance focus on improving efficiency. This presents ethical concerns over individual privacy and autonomy. Caron et al. have highlighted how the increased connectivity in a smart city may permit significant data to be gathered regarding individuals without their consent [94]. Citizens do not have any access to information about the purpose of data collection and the process by which their data are being used. Failure and abuse of security and privacy can threaten public trust and democracy as the required conditions for public trust become deteriorated. Security and privacy enhancement frameworks can help as mitigation strategies [95]. Nonetheless, their social implications of technical fixes have not been thoroughly researched [96].

The concept of smart cities cannot be perceived as objective data collection methods that transparently echo city functioning untainted by ideologies. Kitchin indicates that "data are the products of complex socio-technical assemblages" [97]. This implies that culture, politics, social interactions, and other numerous happenings in cities shape data.

5.3. Environmental Sustainability and Economic Growth

The link between smart city technologies and environmental sustainability is not unidirectional, but complex and uncertain [98]. Positive about smart city projects, some authors have drawn distinctions between economic growth and environmental conservation, stating that smart cities strive to serve both [99,100]. On the other hand, others contest the compatibility of these objectives [17]. Bibri has claimed that the economic dimension prevails over the environmental and social as smart city initiatives are more focused on optimizing the efficiency of solutions, instead of addressing challenges of sustainability [101].

Smart city technologies also necessitate energy usage, and as it embraces the latest technologies such as blockchain, ethical queries about energy consumption begin to rise [93]. Moreover, the development of smart technologies requires scarce elements such as rare earth minerals and metals [102]. The extraction of materials might point to socio-environmental consequences and conflicts in the areas of interest. Their recycling also conveys a considerable challenge [103].

5.4. Conservation of Cultural Legacy in Systems of Smart Cities

Furthermore, for smart city development, typically, technology partners with local authorities and serve as hubs of providing data to ICT connected industries, which previously was inaccessible. Instead of market-led partnership to development of the smart city, which traditionally follows, cities should not serve as the clients for technology companies; rather, they should work as partners in ICT development and deployment. Local society should not be integrated as only a provider of information. However, to facilitate informed choices in the short term, it is required to obtain user-friendly real-time urban data from digital interfaces of varied systems—housing, transport, disaster, traffic. For the empowerment of civil society in the long term, along with input from public officials, populous participation in city planning is crucial for the conservation of natural and cultural legacy.

Involving various stakeholders ranging from those who are making and adding technology to those who are using and purchasing technology can make a smart city successful. Interactions between different stakeholders (technology developers, technology providers, industries, operators, local administrators, government, and consumers) lead to the spontaneous creation of new services and products aimed towards innovative results. ICT development of the urban system that involves informed participants is likely to come with emergent outcomes related to urban sustainability than others [92]. The failure to actively integrate citizens in understanding the smart city can have significant consequences for democracy and may aggravate inequality and prejudice in the city.

5.5. Sub-Systems of Smart City Systems—Beyond the Deployment of ICT

Embracing new technology is not the solution to improving capabilities in a city—there is a need to reconceptualize the roles, practices, and priorities of institutions. Mansoor believes that the notion of a "smart city" should not be restricted to the deployment of just the most up-to-date technology to urban areas. Policymakers must devise and execute knowledge-intensive and innovative policies to establish smart cities on a sustainable basis [21]. These policies must be aimed at improving the socio-economic performance, competitiveness, ecology, and logistics of cities, amongst other things.

Success will be determined by a variety of elements, including adaptive platforms that can alter in response to technological advances, a shift in the behavior of managers, administrators, and people, as well as new modalities of governance, among others. Physical infrastructure such as roads and utilities should be designed in a way that is as modular, replaceable, and upgradable as feasible when developing new cities. When unexpected events occur, this may help to guarantee that life is not disrupted and that daily activities continue as usual.

It is necessary that citizens, software engineers, government leaders, and businesses come to a common understanding of what a smart city should look like and then begin to collaborate to overcome the daunting challenges that they are currently, and will soon be, confronted with in the present and the future. Most importantly, cities can be managed using technology, but they must be created with a vision in mind. To make a city a pleasant place to live, we need "CCTV" to work—citizens, community, technology, and vision [21].

5.6. Suggestions for Improving Systems-Based Simulations of Smart Cities

Some suggestions to improve the results of system models used in literature for smart city applications are noted next:

1. Discussed limitations indicate future research that could include commutation patterns with time-dependency, the consequence of boundary nodes, more elaborated road characteristics, and the model validation with historical data [79];
2. For more precise results of crowd dynamics monitoring, diverse scales at micro and macro levels can be explored;
3. In the area of smart mobility, further work can also incorporate real-time and discrete monitoring at multiple scales, including time and space, through micro aerial vehicles' real-time traffic monitoring [82];
4. Management of scale-dependent institutions is another area of research for better growth of infrastructure [73];
5. Integrating ML with MM to identify both the underlying high dimensionality and low dimensionality dynamics is another opportunity for future research [84];
6. Improving the performance, reliability, and accuracy of multiscale systems uncertainty quantification of multiscale systems in the smart city environment remains open for future work;
7. The implementation of growing approaches for multiscale models in smart city environments is still an open direction for researchers and the industry.

6. Conclusions

In this paper, we have built upon existing literature on the science of the city and presented the smart city as a system of sub-systems (SoS). Specifically, we shed light on the history of urban dynamics, modeling, and formulations to present system science of urban functioning and smart city as a complex system. Moreover, we have provided a comprehensive review of emerging models understanding complex systems of cities. In addition, we have highlighted various developmental and system-related challenges of a smart city. Finally, we have identified the limitations of existing models and highlighted various open research issues that require further development. To the best of our knowledge, no review covers these topics in-depth while highlighting the link and applications of urban models and theories to understand the smart city as a SoS. We also focus on the dynamic issues of smart cities and describe how an understanding of the smart city as SoS can help us better understand and resolve those emerging problems.

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