Urban Computing for Sustainable Smart Cities

Subjects: Computer Science, Interdisciplinary Applications

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The proliferation of ubiquitous computing technologies has led to the emergence of urban computing that aims to provide intelligent services to inhabitants of smart cities. Urban computing deals with enormous amounts of data collected from sensors and other sources in a smart city.

Keywords: urban computing ; sustainable ; internet of things ; smart cities ; intelligence ; big data

1. Introduction

The miniaturization of sensing, computing, networking, and communication technologies in urban spaces has led to the development of new technological ecosystems for smart cities [1]. In present times, city governments are enabling pervasive smart services across all application domains [2], including healthcare, transportation, clean and green technologies, entertainment and leisure facilities, and crowd management, among others [3]. Urban computing can play a critical role in developing smart cities. Decision-makers can work on the urban computing infrastructure to analyse data and make crucial decisions [4]. Improved urban computing can trace the inadequacy of a smart city, and the actors can provide solutions with the potential to mitigate the inadequacy of the smart city. As a result, this increases the efficiency and effectiveness of the smart city, which improves the lives of the citizens living in the smart environment.

In urban computing, data is highly crucial, and the fact is that without data, urban computing can be rendered handicapped without any power of analytics [5]. Data availability is vital to facilitate urban computing in smart cities. Urban computing focuses on improving citizens' quality of life by solving urban problems. Examples of data generation sources include traffic flow, geographical data, and human mobility generated from the city. As an example, the location for setting up a new business or retail store matters a lot. Location has been a matter of survival since ancient times when urban areas were essential to modern cities in the present. A new coffee store set up in a busy place might attract more customers, while setting up the same coffee shop 100 m away may not attract many customers. It is not sufficient to use infrastructure statistics to measure the value of an investment. For example, the noise and pollution coming from trains/bus systems may degrade a coffee shop’s value.

Figure 1 shows the landscape of urban computing in smart cities. The prime objective of urban computing systems is to bring improvements to citizens’ lifestyles and city environments and enrich operational intelligence in smart city services. Urban computing systems provide a complete technological ecosystem to perform end-to-end operations to achieve the aforementioned objectives. To this end, urban computing systems provide computing infrastructures, communication, networking, and data storage technologies to perform data collection, management, analytics, and knowledge visualisation operations. The researchers [6], divided the technology ecosystem for urban computing into five categories: (i) sensing, (ii) data management, (iii) data fusion, (iv) handling sparsity, and (v) knowledge visualization.

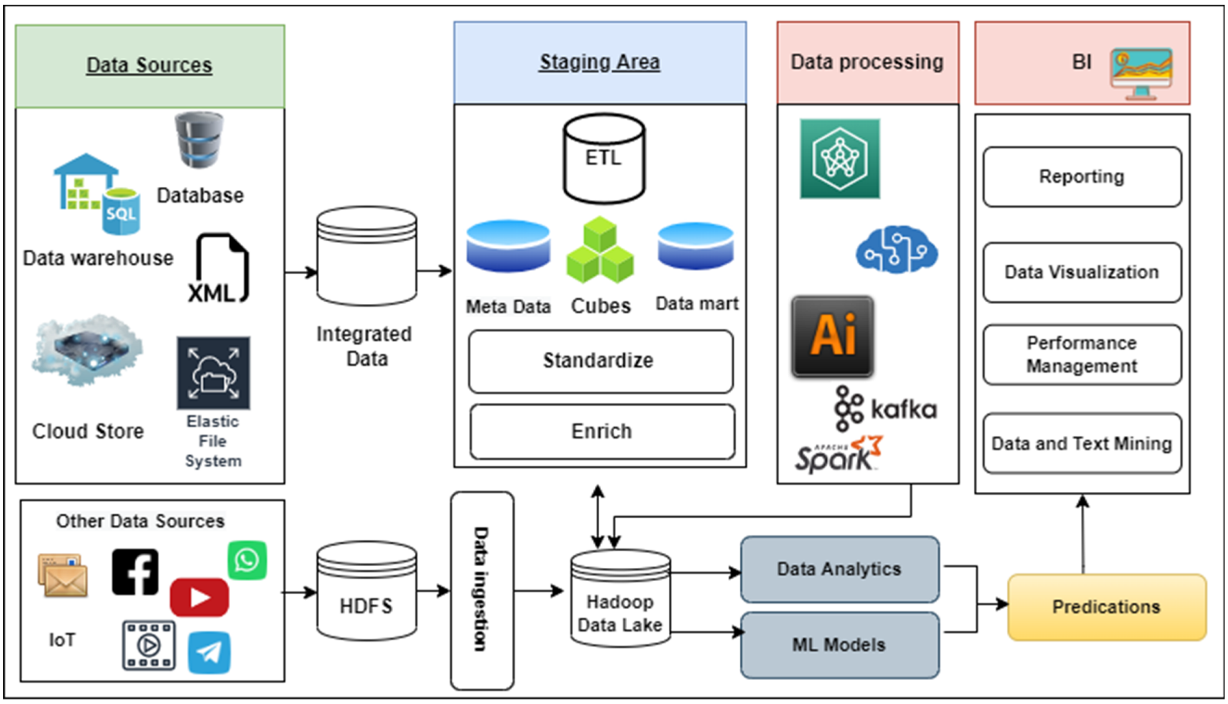

Figure 1. The landscape of urban computing in smart city environment.

Urban computing typically facilitates the development of smart cities by integrating all the vital components of the smart cities as an ecosystem. It provides necessary technologies for the adequate distribution of services to citizens through different city systems in smart cities. It addresses the complex problems of smart city service delivery. As such, urban computing can play a significant role in smart cities in the technological dimensions shown in **Figure 2**. Seemingly, the eight dimensions look diverse in terms of computing technology and its applications.

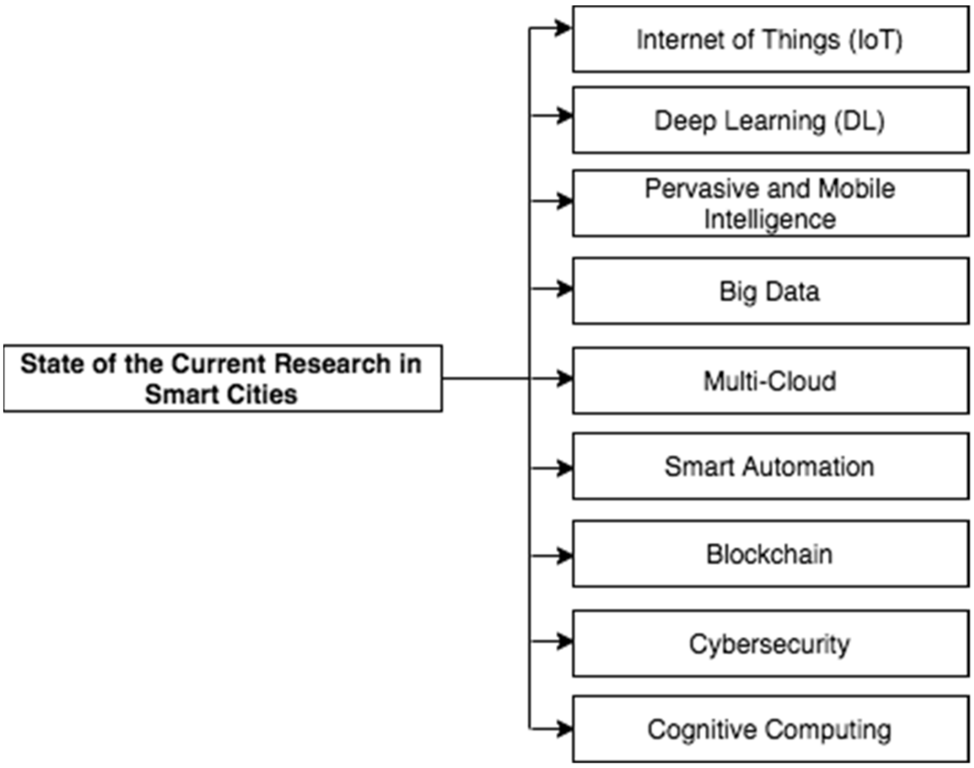

Figure 2. The current state of research challenges in smart cities.

IoT: The IoT has emerged as a source of data generation through interconnected complex systems of various sensors and smart applications interacting with each other in a city environment [7]. These interactions range from specific domain applications to more advanced cross-sectoral systems [8]. IoT-enabled smart cities respond to citizens' necessary wants to create smart cities [9]. For example, to enhance the existing bus services in the United Arab Emirates, [10] introduced optimised energy consumption based on a smart IoT-friendly environment. The approach is to estimate bus stop occupancy and lights, automatically report utility breakdowns, remotely monitor air conditioning, and measure the air pollution around

Deep Learning (DL): Solving urban problems may require a deep learning approach to generate large values through urban computing. Many studies have incorporated deep learning into smart city applications to uncover new information from big urban data [9][11]. Refs. [9][12] explored deep learning in the fusion of urban big data. The study focused on classifying urban big data fusion into three categories based on deep learning: (i) DL-double-stage-based fusion, (ii) DL-output-based fusion, and (iii) DL-input-based fusion. However, some urban big data fusion challenges were highlighted, such as data quality, multi-modal data, spatiotemporal data, and data sparsity. Niu et al. [13] implemented traffic prediction using a deep learning architecture using traffic flow data that were spatiotemporal. Another example of deep learning is the study on urban water flow and water level prediction proposed by [14]. In addition, mitigating the effects of temperature on the characteristics of wireless communication links motivated [15] to propose a reinforcement learning-based sleep-scheduling strategy for wireless sensor nodes. Reinforcement learning enables a node in a network to react based on the current environment in order to take action, such as transition, listen, or sleep, autonomously. The results of sustainable operations indicated good performance compared with the baseline network operation and connectivity algorithms. The main challenges of adopting deep learning for urban computing in smart cities are coping with time dependency, dealing with large amounts of data with various formats, fast-moving streaming data, and the trustworthiness of data analysis [16].

Big Data: The concept of big data has been utilised in urban computing due to the growing amount of data that increases every day via various sensors embedded in smart cities [17]. Large datasets are generated utilizing IoT and ICT technologies employing routine and autonomous sensing, which replaces the traditional approach [18]. In smart sustainable cities, IoT-enabled urban data are increasingly related to regular or automatically sensed data. Furthermore, ubiquitous sensing is a key component of future smart sustainable cities, which often rely on the realization of numerous ICT visions of ubiquitous computing, particularly the Internet of Things. Honarvar and Sami (2019) [19] published data on urban computing so that knowledge extracted through integrating multiple independent sources in smart cities can be accessed. The data relating to urban computing were collected in Aarhus, Denmark from multiple sources, including static and dynamic sources. The period covered for the data collected was from first of August to 30th September 2014, covering an area of 91 square KM with an estimated population of 270,000. The static sources provided data on the use of land, water barriers, waterways, amenities, points of interest (POI), buildings, and roads. On the other hand, the dynamic data sources included parking lots, weather, pollution, and traffic. The static data were collected and pre-processed from online sources, while the dynamic data were collected using 217 sensors embedded within the city. The data can provide valuable contributions to urban computing by considering both dynamic and static data sources in smart cities. The data can be utilised to gain new knowledge for improving urban planning and making better decisions. Researchers can use them to investigate the spatial features of different events in smart cities [19].

Multi-Cloud: Multi-cloud-based computing has become a substantial technology for smart cities and urban computing. It recently emerged from the traditional computational paradigm, moving to a more sophisticated multi-cloud environment, especially when processing large amounts of data. Dhirani, Newe et al. [20] discussed various SLA issues with respect to hybrid multi-cloud environments and offered possible solutions for how companies can adopt them in their management processes. Currently, many smart city technology providers are encountering difficulties in managing multiple clouds that reside within different vendors running on different platforms, computational requirements, and vendor SLAs [20]. Moreover, [21] explored the role of cloud computing, which can play a significant role in assisting cities in becoming smart.

Smart Automation: Smart devices are increasingly changing our daily lives in urban areas [22]. For example, smartphones can be used in smart healthcare systems to perform measurements of several physiological parameters by utilising wireless medical devices, such as a spirometer, electrocardiogram, and oxymeter, that are connected to the smartphone gateways through a Bluetooth connection. Meanwhile, smart cities are developing rapidly by introducing new practices and services. It is currently expected that to comprehend a smart city's commitment to overall urban planning and vice versa, it is necessary to recognise urban planning offerings to a smart city environment. Large cities worldwide have overstressed/outdated infrastructures facing challenges in delivering crucial civil services to their populations. These civil services are essential, especially for people with disabilities. The cyber-physical concept is proposed by [23] to facilitate the lives of people with vision loss or other special needs. The proposed concept with real-time information exchange will function as a bridge between cyberspace infused with the IoT and physical space. This will help people with disabilities to navigate through streets and street crossings as well as warn individuals who are in danger. The proposed solution is a distributed system that allows flexibility in smart agents and a smart environment, but it does not include the liabilities and cybersecurity of the system. The system provides ample opportunities for researchers to consider new assistive approaches to aid people with disabilities with orientation, navigation, and mobility.

Blockchain: Blockchain as a technological innovation allows for decentralisation, persistency, anonymity, and auditability in a smart city environment [24][25]. The main challenges of blockchain in smart cities are scalability, flexibility, and security [26]. In their book on smart blockchain, Krishna, Ravi et al. [27] surveyed 33 papers to identify the relationship between analytics and blockchain in order to enhance its overall performance in numerous real-world problems. The study focused on highlighting the importance of analytical tools for the design and implementation of blockchain in a smart city environment. Ref. [28] designed an infrastructure using the blockchain mechanism in order to facilitate the implementation of security and privacy based on spatiotemporal smart contract services to help improve the sustainability of mega smart cities. The infrastructure concept utilises cognitive fog nodes at the adage to host and process offloaded geo-tagged multimedia payloads and transactions from a mobile edge and IoT nodes

Cybersecurity: Cybersecurity continues to be a serious issue for many smart city applications in cyberspace due to the number of security breaches, particularly man-in-the-middle and zero-day exploit attacks. This has resulted in the need for producing new theories to understand, reason, and learn from such attacks, as traditional machine learning systems face the difficulty of detecting small mutations in these attacks over time. Moreover, the weapons and defences being used are moving at breakneck speed, and the attack surface is rapidly expanding. Protecting data requires dealing with hacking attempts in which machine learning can be used to detect security threats. Meanwhile, traditional security tools utilise known threat signatures and threat feeds supplied by trusted partners. This is not sufficient in the present day as enterprise perimeters are dissolving, and the first sign of a new and unknown threat may be recorded in an application log or with a user session-monitoring tool.

2. Urban Computing for Sustainable Smart Cities

2.1. Urban Data

With the potential increase in the global population, the world is moving fast towards urbanization. According to some studies [29][30] most big cities and towns are leaving a sustainable environmental impression. Unsustainable development drives innovation in areas such as economic creativity, turning economic innovations into results, and providing platforms that can safely propel the development of urban communities. Information and communication technology (ICT) is a sacrosanct instrument for propelling the design and development of devices for an urban community [31][32].

The ability of users to adapt to this environment can be aided by the users' understanding of the operation and use of the technologies embedded in the urban community. Smart devices and mobile phones perform the collection of statistical data to increase geometrically in view of the fact that urban life activities are captured [33]. As a result of this, both government and non-governmental organizations were prompted to initiate innovations using these data to improve quality of life. Emerging research studies with overlapping themes and issues around urban computing have become a reality due to recent breakthroughs and the emergence of low-cost sensors, actuation and smart automation, nanotechnology, and wireless communication [34]. Our lives now revolve around smart devices that are always connected to the internet due to pervasive computing technology, changing how we interact with one another and conduct business in smart cities [35][36]. However, urban computing programs have given residents of smart cities technological and social options. According to [37], effective parking systems can be developed based on the data generated from an urban community to alleviate traffic congestion. Thus, this motivated the researchers to develop SmartPark for embedding in San Francisco communities. The technology uses a ubiquitous cellular and Wi-Fi infrastructure to deliver real-time parking availability information to automobiles.

Furthermore, with the growth and development of the internet, mobile devices, and sensor technology, data can be generated for urban computing. For instance, customers can use mobile applications to post ratings or comments about a product or service after consuming or using a service. With regard to mobility data (these data can be user reviews and traces of location), smart card transaction traces and commuter daily commute records obtained through a taxi GPS can be utilised to determine the proper location for setting up a retail store in a city [38].

2.2. Opportunities

2.2.1. Simulation Modelling

Simulation modelling is mainly used to predict the performance of a physical model by creating and assessing a digital prototype of the model in a smart city environment. It explains a system and the conditions in which this system can withstand vulnerability, allowing researchers and practitioners to have flexibility in designing the system as they can determine the efficiency and correctness of the system before the actual construction. Simulation modelling also allows researchers to study a problem at various abstraction levels and makes it easy to replicate for further studies. Simulation modelling is the key approach used to create and assess various urban computing models [39][40][41][42].

2.2.2. Urban Mobility

Urban mobility is regarded as the key to achieving sustainable development goals, and it drives both economic development and social development [43]. Mobility is the core component of a smart city because transportation provides vast amounts of citizen and vehicle data. Authorities are proposing mobility plans with a shift towards sustainable transport models, and urban transport is embracing the sharing economy via public and private initiatives [44]. The challenge is militating against sustainable urban mobility, which is a source of concern for urban planners and policymakers because it is multi-dimensional, covering environmental performance, energy efficiency, the monitoring of behaviour and mobility, and the influencing of economic development [45][46][47]. Another challenge in implementing sustainable urban mobility is integrating urban mobility systems and smartphone-enabled mobility services and modernising public transit services. Other urban mobility challenges include growing traffic congestion, quality of air reduction, physical inactivity, and reachable, reliable, safe, and affordable public transportation, as well as new homes and job creation [48].

2.2.3. Ubiquitous Cities

Ubiquitous cities (u-cities) are an advanced level of smart cities with intelligent convergence systems. A u-city is a solution to problems confronting urban communities, such as weak security, poor levels of sustainability, and pollution. To determine the requirement for the platform to establish a u-city, Rad et al. [49] propose an effective conceptual framework that explores and measures the major indicators for a smart city, i.e., environments, citizenry, and infrastructures that are critical. A Tehran, Iran and Seoul, South Korea ubiquitous coefficient was computed. The results verified the robustness and effectiveness of the proposed framework's accuracy in determining the ubiquitous conditions of the cities.

2.2.4. Outliers Detection

Knowledge extraction is a crucial task in urban computing for smart cities and becomes more significant when there are outliers in the big data. Souza, Aquino et al. [50] proposed a method for outlier detection by using the multiway nature of the data. The proposed method detects the outlier in big data by reducing dimensionality, classifying latent factors, and combining both. The method was applied to four urban cities, and the outcome indicated that the proposed method produces a new clustering approach. The results are more accurate, and it takes data from different dimensions. The proposed method can also be integrated with other applications such as a cloud and further extended by adding more information such as climate, meteorological data, quality of water, etc.

2.3. Key Applications

Intelligent Transportation: Intelligent transport systems (ITSs) are among the major components of any urban computing smart city [51]. Large-scale WSNs are used in intelligent transportation to monitor journey time online (including routing choices, wait times, air pollution, traffic jams, and noise emissions) [52]. Different modes of transportation, cutting-edge infrastructure, and solutions for traffic and mobility management are all creatively offered by ITSs. ITSs have transformed the way and manner in which people commute in urban smart cities [53]. IT is a novel transportation technique embedded with electronic equipment including wireless and communication systems for users to have easy access to smart, safe, and fast travelling channels. Some major features of an ITS include route information (it provides prior real-time information about travelling routes to users and enables them to decide the best route), safety and vehicle control (it enables drivers and also warns them about their driving proficiencies, road conditions, and vehicle performance), and electronic timetables (it provides travellers with detailed information concerning the arrival and departure times of vehicles, trains, etc.) [54]. An ITS provides a suitable and comfortable living environment for people in smart cities by minimising the level of pollution and providing smart parking solutions [55].

Smart Building: A smart building is embedded with ICTs and services by equipping appliances in the house through networks to improve living quality. Typically, an enterprise of intelligent devices is embedded in a smart building to offer unique services at home that are typically absent in conventional buildings for the benefit of the users [56]. It uses technology to equip devices powered via energy efficiency, cost-effectiveness, and Wi-Fi. These devices are used for intelligent monitoring and remote control that automatically provide harmonic interaction between them without human intervention [57]. A cyber-physical system (CPS) is a typical illustration of a smart building [58][59] providing comfort, a secure environment and safety, low power consumption, and ubiquitous convenience. Smart building services can be further improved by adding health functionalities to the cloud services, such as the issues of blood pressure and heart rate, that are typically not feasible to have in systems embedded locally [60].

Smart Vehicles: Because of the increasing rise in urban communities, smart cities have attracted a lot of interest. With the developing nature of smart city environments, different smart objects are integrated together and transformed into smart systems [61]. To leverage the present challenges such as pollution and energy consumption imposed on a smart city, vehicular cloud computing is provided. Recently, the rapid evolution in terms of "automotive technology and on-demand transportation services" in smart cities has led to the development of smart vehicles [62], which are equipped with wireless connectivity and autonomous capability to reduce the level of carbon production in smart cities. A smart vehicle is a major enabler for smart city environs because it is equipped with additional onboard gear to enable on-demand services for vehicle occupants [63]. Smart vehicles are implemented using IEEE 802.11.p and IEEE 1609 standards [64] that enable communication and the retrieval of information from the vehicle's environs. Given the importance of smart vehicles in a smart city environment, there has been an increase in the adaptation of vehicle-to-vehicle communication, allowing vehicles to exchange information. As such, vehicles can transmit certain information such as destination and speed wirelessly without human intervention. Messages and warnings alert a driver to the need to control vehicle movement to avoid an accident. Sending messages, such as that he is more than 300 m away, can inform a driver about different conditions such as traffic, weather, threats, and information that is of general use [65].

Smart Mobility: Urbanisation introduces new challenges to a smart city project in the 21st century and has prompted problems such as traffic, pollution, and transportation systems [66]. These problems have prompted stakeholders to explore data as a result of operations in urban areas, such as power consumption, congestion as a result of traffic, etc. Smart mobility is a system that makes decisions about traffic and pollution based on the data extracted on traffic and pollution. Subsequently, routes are recommended according to the preference of users or to ease traffic congestion. Smart mobility has the capacity to make a smart city look attractive and beautiful and promote business expansion by easing the flow of traffic in the smart city [67][68]. An intelligent mobility approach is required to guide and support inhabitants living in smart cities [69]. Different preferences differ among pedestrians, motorists, and cyclists in view of the fact that some prefer a route without crowds no matter the distance to the destination, while others prefer the shortest possible route regardless of crowds. On the other hand, some prefer the route with minimal pollution because of health complications or low-quality air [70].

Smart Grid (SG): An SG is a power system with operational and energy measures that are integrated with a communication infrastructure to provide energy flow in a bi-directional manner and information [71]). The tremendous energy demand in smart cities has ushered in the SG evolution [72]. An SG is a smart electrical distribution system with various power functions, including smart meters, sustainability of energy, smart machines, and energy effectiveness. The energy properties are responsible for the energy distribution flow in a bi-directional manner between manufacturers and users [73]. SGs are currently adopted across the world to achieve sustainability objectives and secure and economic power supplies with users that are active in participating in using advanced metering infrastructure as well as home energy management [74]. The general packet radio service is an SG communication technology used for long-distance data transfer over a circuit switch [75]. An SG that operates globally has to use microwave access technology that uses IEEE 802.16 that provides long-range data transfer services and monitors the network's status [76]. Another communication technology of SGs is Bluetooth (IEEE 802.15), which has a low power consumption ability and operates with a frequency of 2.4 GHz to manage and monitor the power system. ZigBee (IEEE 802.15.4) is an application generally accepted in SGs because of its high level of energy efficiency, which makes it consume energy at a lower rate [58].

Smart Communities: Smart communities are the basic components of a city [77] that uses connected technologies to improve smart city infrastructure, regardless of the size of the city. A smart community involves city planners who monitor and collect traffic data to improve the city's transportation system and the community's competitiveness [78]. The collected data lead to implementing the new transportation system within communities to reduce the rate of accidents and travel times. A study by Kulkarni and Farnham [79] predicted that by 2020, the value of smart communities in the global market will be approximately $1.6 trillion. In addition, smart communities have the potential to significantly boost community life by enabling people to react to environmental changes and earn a living and empowering them to contribute to society [80].

2.4. Implications

Security: The communication technologies used for effective communication in urban computing in smart cities are WSNs, RFID, Wi-Fi, 4G LTE, LTE-Advanced (LTE-A), and 5G [81][82]. Each of these technologies is exposed to different security issues due to the components used in developing them. For WSNs, sensors and actuators are the main elements that make WSNs flexible and incur high communication latency. These characteristics make WSNs prone to cyber-attacks [83]. However, in a smart city, the security related to the WSN can be based on the confidentiality of data, authentication, integrity, and freshness. The four security issues related to WSNs can be mitigated based on cryptographic algorithms, management, routing that is secured, and trust of the node [83]. For RFID, the possible security issues that arise from RFID are tracking, DoS, repudiation, spoofing, alteration, corruption and deletion, eavesdropping, and counterfeiting. For urban computing in smart cities, RFID technology is mainly used for the automated exchange of information without any manual involvement and can work in harsh environments [84].

Privacy: The vision of a smart city is to improve facilities in urban areas with the incorporation of technological tools into facilities such as the SG, transportation system, government institutions, schools, etc. [85], to enhance living standards wirelessly. With the mode of communication among connected devices in smart cities, data privacy poses a major challenge in the network because data intrusion from malicious devices can temporarily stop the services provided by the smart city [85].

Ethics: Ethical evaluation is the fundamental component required for the acceptance of smart city technologies. Urban computing and smart-city-enabled technologies have become essential components for urban city functionalities [86]. Urban operational controls and city services are becoming highly responsive to data-driven modes. As a result, there is a need to design and deploy ethics for both users and smart city application developers. Some of the main ethical designs involve personal privacy, obtrusiveness, stigma and autonomy, and data sharing and autonomy [86]. Personal privacy has complex phases [87].

Data sharing and autonomy involve the right of users to make personal decisions with respect to freedom and independence, specifically in reference to assistive technologies such as smart homes, SGs, power plants, etc. It deals with the aspects of privacy that are not directly connected to the control of data, and it includes both physical and social aspects [88]. However, privacy is the major prerequisite for autonomy [86][88].

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