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Review

Urban Computing for Sustainable Smart Cities: Recent Advances, Taxonomy, and Open Research Challenges

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Abstract: The recent 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. In this article, we investigated and highlighted the role of urban computing in sustainable smart cities. In addition, a taxonomy was conceived that categorized the existing studies based on urban data, approaches, applications, enabling technologies, and implications. In this context, recent developments were elucidated. To cope with the engendered challenges of smart cities, we outlined some crucial use cases of urban computing. Furthermore, prominent use cases of urban computing in sustainable smart cities (e.g., planning in smart cities, the environment in smart cities, energy consumption in smart cities, transportation in smart cities, government policy in smart cities, and business processes in smart cities) for smart urbanization were also elaborated. Finally, several research challenges (such as cognitive cybersecurity, air quality, the data sparsity problem, data movement, 5G technologies, scaling via the analysis and harvesting of energy, and knowledge versus privacy) and their possible solutions in a new perspective were discussed explicitly.

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

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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. Ref. [5] presented a survey on smart cities that covers the smart city motivation and the architecture, characteristics, features, and composition of smart cities. Case studies of New York, Santander, London, San Francisco, Barcelona, Nice, and Padova are discussed as smart cities.

Ref. [6] presented a discussion on the Sense–Analyze–Actuate paradigm for smart cities, outlining technical problems and potential solutions for controlling city-scale resource infrastructures. Later, [5] paper presented the challenges and future directions for research that can further develop smart cities. Furthermore, sustainable cities are complicated systems that make it difficult for smart cities to successfully challenge the complexities by using big data technology to monitor, analyse, and improve performance in terms of sustainability. Ref. [4] examines and discusses the enabling role of urban computing and intelligence in tactics and its inventive possibilities.

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 [7]. 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.

Ref. [8] propose the Urban Mobility Project Sustainability Index in Brazil to monitor and evaluate the sustainability of urban mobile projects. The project identified the possibility of introducing changes in Brazilian urban mobility policy. Moreover, the influence of urban planning on landscape changes and social behaviour is in line with the urban sustainability project-17 sustainability indicators identified and grouped based on their relationship with the environment and social and economic features. Moreover, [9] presented a broad review of smart and sustainable cities based on fundamentals, assumptions, current development, emerging technological trends, and planning for future practice. The designs of the sustainable city models and smart city approaches were discussed, including strengths and weaknesses in the context of sustainable development goals. An integrated approach for sustainable city modelling from a theoretical perspective integrated with the current wave of computing, big data, and context-aware computing technologies was proposed based on the challenges identified in a survey for future practice in smart sustainable urban planning and development [10]. The article also highlighted unresolved challenges as opportunities for future research.

In terms of achieving information system success, according to Chatterjee et al. [11], the growth of wireless technology integrated with the IoT and artificial intelligence (AI) helped to simulate intelligent behaviour and make accurate decisions without human intervention. It also enhanced the use of IoT devices as citizens connected to the internet.

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 [12], 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.

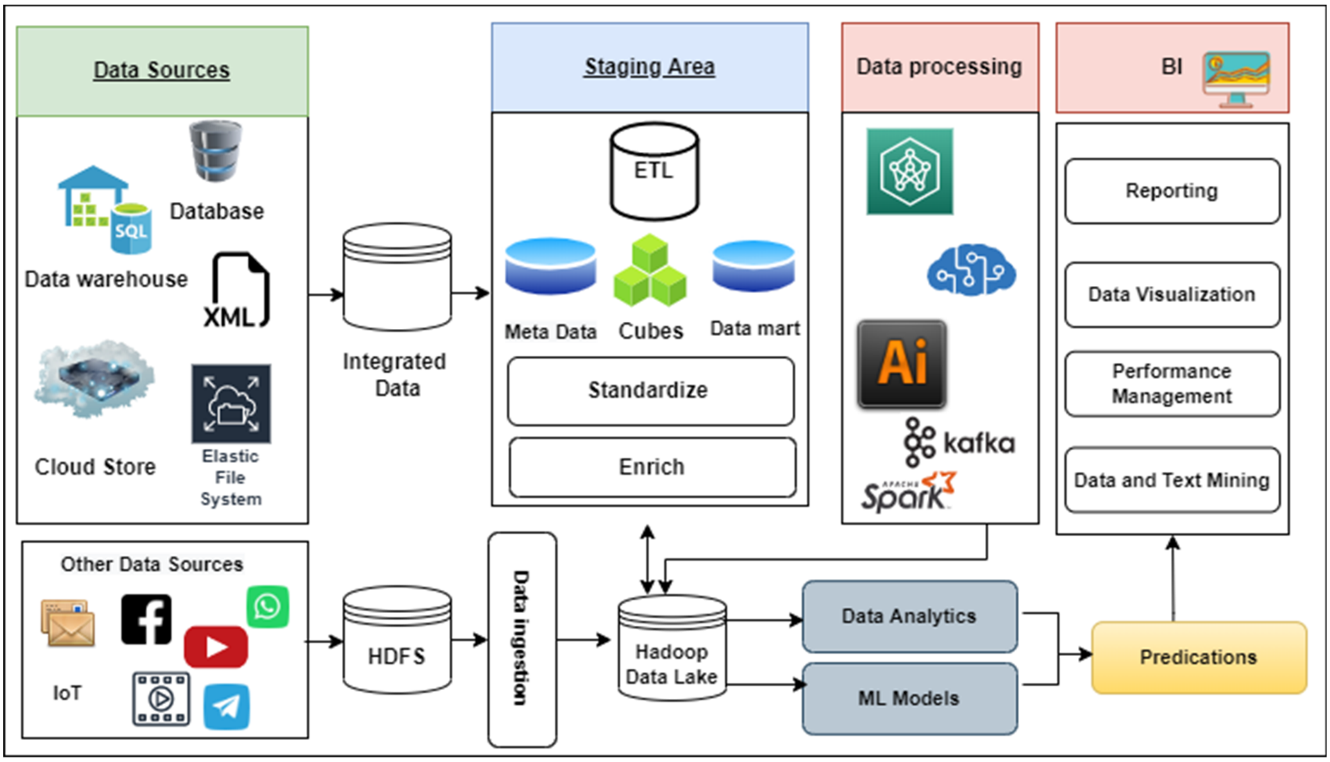

Figure 1. The landscape of urban computing in smart city environment.

However, we still need to handle several communication-related challenges, including privacy concerns, security threats, computational burdens, bandwidth utilisation, and energy efficiency.

In this study, we propose to explore the role of urban computing in smart cities.

The detailed contribution of this study is listed as follows:

- This study proposes a classification to categorise the existing literature into multiple dimensions linked to the present current research issues in the smart cities paradigm. The primary issues connected with each category of urban computing are highlighted based on a literature study of recently published studies. To simplify this procedure, we have identified nine technologies: deep learning, big data, pervasive and mobile intelligence, multi-cloud, cognitive computing, smart automation, blockchain, cyber security, and the Internet of Things.
- We built a taxonomy of the most pertinent urban computing and smart city literature based on urban data, methodologies, applications, supporting technology, and implications. Each parameter was studied independently, and the key results were presented for the purpose of constructing effective smart urban computing sustainable city contexts.
- We qualitatively analyse the role of urban computing in smart cities by providing several applications and technologies, such as intelligent transit, smart homes, and smart automobiles.
- Using significant use cases, such as energy consumption, transportation, government policy, and business process, we demonstrate the significance of urban computing in smart cities.
- We cover several unanswered research questions affecting the future growth of urban computing in smart cities. Using data from the published literature, we determined that the following research topics—cognitive cybersecurity, air quality, IoT resources, cyber-physical system, data sparsity, data movement, 5G technologies, scaling via the analysis and harvesting of energy, and knowledge versus privacy—could be potential key research areas in the advancement of urban computing for smart cities.

- Concise summaries of these contributions are outlined in separate sections, from Sections 2–6, while Section 7 provides concluding remarks.

2. Methodology

The methodology for the review in developing the article shows the approach used for conducting the literature review. The literature review stages are listed as follows: keywords formulation, identification of the academic search engine and bibliographical databases, screening of the articles, exclusion and inclusion criteria, and eligibility for selection. The keywords were formulated based on the objective of the study. The final keywords formulated were "Urban computing", "smart city", "urban city", "smart cities", "smart cities & sustainability", "Internet of things", "sustainable city", and "sustainability". The academic search engines relevant to computing used the keywords to identify highly relevant articles. The academic search engines used were IEEExplore, Web of Science, ACM Digital Library, DBPL Computer Science Bibliography, Ei-Compendix, ScienceDirect, Scopus, and SpringerLink. The study excluded papers written in other languages; only papers written in English and peer-reviewed articles published in journals, conferences, and edited books were selected for inclusion. The articles retrieved from the academic search engine and bibliographical databases were screened based on each article's title, conclusion, abstract, and duplicates before fully assessing the complete contents of the papers that passed the selection criteria.

3. State of the Current Research

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. This paper highlights the recent research challenges related to smart cities. The main contribution of this paper is to show the interdisciplinary nature of urban computing besides being state-of-the-art. We divided urban computing for smart cities into eight technological dimensions—IoT, deep learning, big data, multi-cloud, cognitive computing, smart automation, blockchain, and cybersecurity—as illustrated in Figure 2. Given the keywords formulation, the selection of these dimensions was conditioned by two factors: (i) the relevant articles that include urban computing, smart cities, and any of the nine dimensions in the title, and (ii) the relevant articles that include urban computing and/or smart cities with any of the nine dimensions in the title, abstract, or keywords.

Table 1 provides a summary of the current 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 [13]. These interactions range from specific domain applications to more advanced cross-sectoral systems [14]. IoT-enabled smart cities respond to citizens' necessary wants to create smart cities [15]. For example, to enhance the existing bus services in the United Arab Emirates, [16] 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 the area. The idea is to connect various sensors and actuators via a Wi-Fi-based standalone microcontroller.

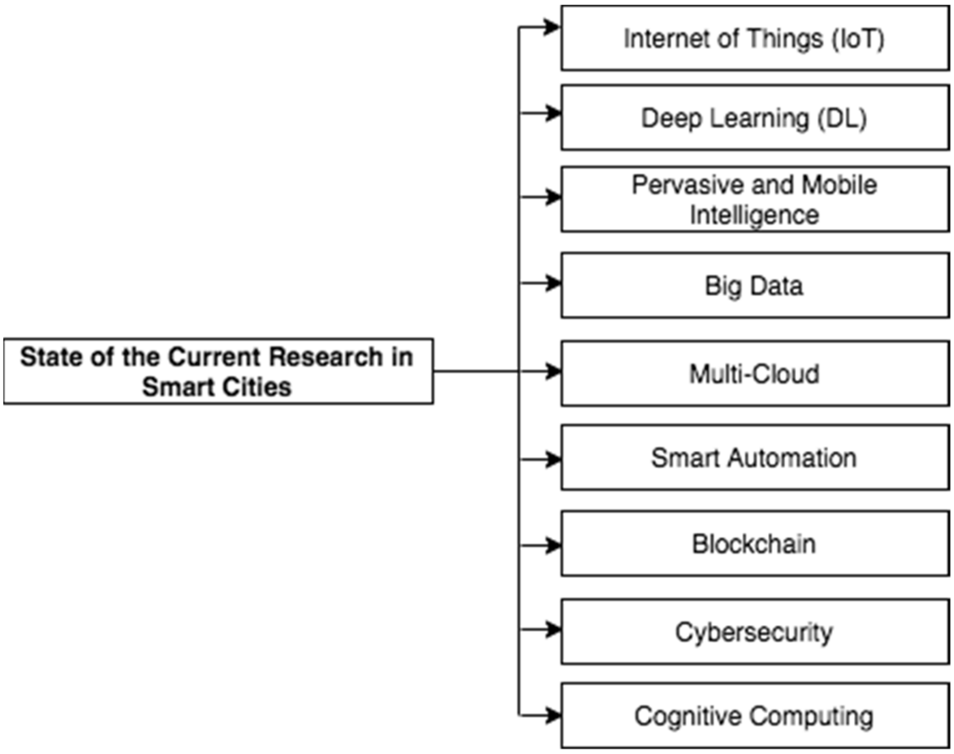

Figure 2. The current state of research challenges in smart cities.

Table 1. A summary of the current research challenges in smart cities.

Research Area	Key Challenges
Deep learning	• Coping with time dependency • Optimisation metrics
Big data	• Coping with heterogeneity and integration of heterogeneous sources • Coping with noisy, uncertain, and inconsistent data
Pervasive and mobile intelligence	• Performance issues • Energy-efficient • Programming support • To design processing device equipped with trust, security, and privacy
Multi-cloud	• Develop and run composite applications on the cloud • Re-usable software components with an online library to provide various urban computing services • User authentication • Standardisation
Cognitive computing	• Computation efficiency • Implications • Truth
Smart automation	• Energy efficiency • Scalability
Blockchain	• Modelling • Scalability • Usability • Auditing
Cyber security	• Data Bias in social media datasets • Cryptography with low energy consumption
IoT	• Urban sensing and data acquisition • Battery and processing power

In an IoT-based platform designed for the real-time monitoring of elephants within a forest's boundaries, the system incorporated cognition and computational intelligence techniques. Moreover, [17] developed a boundary intellect integrated with a network of wireless sensors to detect elephants in a forest to prevent conflict between elephants and human beings. The system was deployed in a forest in India and can detect elephants entering or crossing the border with a 50 m accuracy. The system has the potential to reduce human–elephant conflict within the forest.

Janssen et al. [18] reported the challenges of the IoT. They summarised the adaptation and implementation of the IoT in smart cities and discussed issues such as standardisation and network flexibility issues, sensor mobility, and the accuracy, timeliness, and completeness of the collected data.

The fundamental IoT technologies and architectural framework are shown in Figure 3. The framework combines numerous layers, with the first layer containing sensors and objectives utilized in diverse domains, such as hospitals, banks, factories, government offices, agriculture, etc. These sensors are connected to several network technologies, including optical fibre, ethernet, 4G/5G, LTE, Wi-Fi, ZigBee, and Lora [19]. The cloud storage solution provides scalable and cost-effective storage for network-collected data. The upper layer is viewed via numerous IoT applications consumers utilise to enhance security and efficiency.

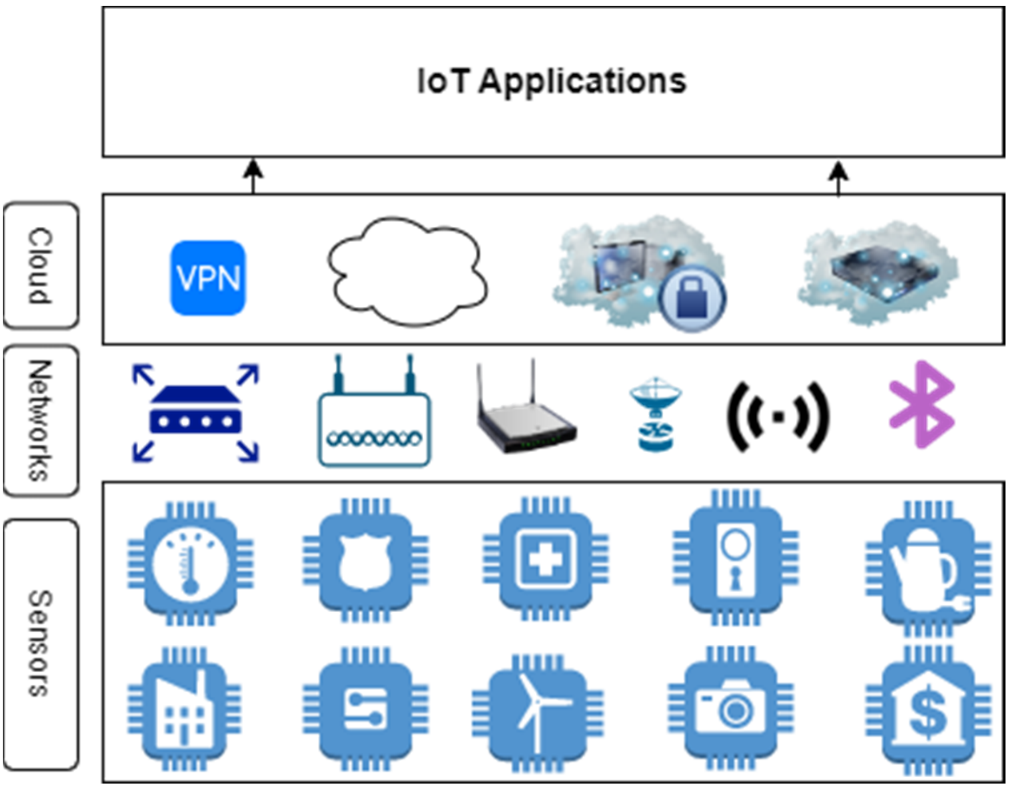

Figure 3. IoT technologies and architectural framework.

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 [15,20]. Refs. [15,21] 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. [22] 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 [23]. In addition, mitigating the effects of temperature on the characteristics of wireless communication links motivated [24] 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 [25].

Pervasive and mobile intelligence: Pervasive and mobile intelligence is landscaping the overall path to a smart world by being used in physical environments for providing reliable and relevant services to people. Pervasive and mobile intelligence allows the development of new applications and systems and significantly expands the range of computing opportunities, including digital intelligence in everyday items and homes. It can simplify and improve efficiency [26]. Usman and Gutierrez [27] presented a survey on the issue of trust in pervasive and mobile computing. The survey tried to provide a comprehensive concept and definition of trust from different areas of study to propose the concept of management toward trust-based protocols in pervasive and mobile computing. Current trust-based protocols were critically evaluated. The article addressed the techniques, methodologies, models, applications, and needs for trust-based protocols.

The security of bridges in trust-based protocols for pervasive and mobile computing and approaches for evading security bridges have been vividly discussed. Open research problems in the context of trust-based protocols in pervasive and mobile computing have been outlined [28]. Ref. [29] presented a case study in mobility management related to pervasive computing and sustainable development. The authors highlighted an example wherein cultural resistance has forced pervasive computing to change through incremental and non-intrusive applications. The example gives a real-time view associated with a public transportation system while utilising mobile phones. The results show that pervasive computing supports introducing new products that allow positive social changes regarding behaviour and values. In addition, in the quest to know whether daily stress can be reliably measured using human behaviour metrics that are retrieved from a mobile phone, Bogomolov et al. [30] proposed a new approach to do just that. The results of the work were analysed based on two algorithms, Random Forest and Gradient Boosted. The results show that the impacts of such technology are of reducing stress and further enhancing subjective wellness for sustainable living. However, the work is lacking in predicting mobile users' personalities and detecting stress in an entirely automated way.

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 [31]. Large datasets are generated utilizing IoT and ICT technologies employing routine and autonomous sensing, which replaces the traditional approach [32]. 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) [33] 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 [33].

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. [34] 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 [34]. Moreover, [35] explored the role of cloud computing, which can play a significant role in assisting cities in becoming smart. The authors identified some of the research challenges associated with cloud computing with respect to urban computing for smart cities, and these challenges are summarised as follows: (i) develop and run composite applications on the cloud; (ii) the re-usable software lirary development that houses re-usable software that provide various services to process requests; (iii) user authentication; and (iv) standardisation.

Smart Automation: Smart devices are increasingly changing our daily lives in urban areas [36]. 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 [37] 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.

Moreover, the smart grid is one of the largest IoT systems in a smart city. Researchers' general focus has been on improving the internal system functions of the smart grid, but they are not focusing on developing urban computing based on smart grid data [37]. A ubiquitous urban computing framework was proposed using smart grid data. The system is based on a stochastic configuration network and robust principal component analysis. Shop location resettlement and a shared bicycle system were performed as the applications of the proposed system. The results show that the proposed method provides a near-optimal solution for demand scenes in a smart city. The authors argued that a smart city could be used as feedback for other data resources in the smart city, and along with the proposed system, it can be of great help in power distribution systems.

Blockchain: Blockchain as a technological innovation allows for decentralisation, persistency, anonymity, and auditability in a smart city environment [38,39]. The main challenges of blockchain in smart cities are scalability, flexibility, and security [40]. In their book on smart blockchain, Krishna, Ravi et al. [41] 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. [42] 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.

Interestingly, security is one of the strengths of blockchain [43]. However, researchers thoroughly question it due to blind trust in blockchain developers and other stakeholders as well as issues and threats to cybersecurity [44,45]. Other challenges include computational efficiency and storage size, interoperability [46], and usability [47]. In general, researchers argue that these challenges in adopting blockchain stem from the immaturity of the blockchain [40].

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.

Cybersecurity is the most crucial challenge of urban computing for smart cities as it relies on technology to work with the intertwined ecosystem. An increase in technology assists urban computing in an embedded computing capacity, which has led to a rapid expansion of diverse smart devices in smart city umbrellas [48]. While these new devices and urban computing applications offer great utility for the public, they also open up a broader attack space for malicious cyber-attacks [48,49]. Researchers a rgue that cybersecurity is needed in all embedded layers of smart cities to mitigate these security challenges [50].

Cognitive computing: Cognitive computing has become visible in improving the quality of life in cities [51]. In a paper by [51], the relationship between smart cities and cognitive computing is discussed in order to identify how smart cities can utilise the power of cognitive computing to design cognitive cities. Ref. [52], classified cognitive computing into three critical technologies for smart cities: the IoT, big data analytics, and cloud computing. They underline that the enabling approaches for these technologies are reinforcement learning and deep learning. Such integration may drive machines, humans, and cyberspace towards more intelligent services in urban cities. The main challenges associated with cognitive computing in a smart city with respect to urban computing are presented in Table 1.

4. Taxonomy

In this section, we devise a taxonomy of urban computing in smart cities based on various categories. These categories demonstrate the interrelation between the urban computing concept and smart cities. Figure 4 shows a number of parameters extracted from the literature: urban data, opportunities, key applications, and implications.

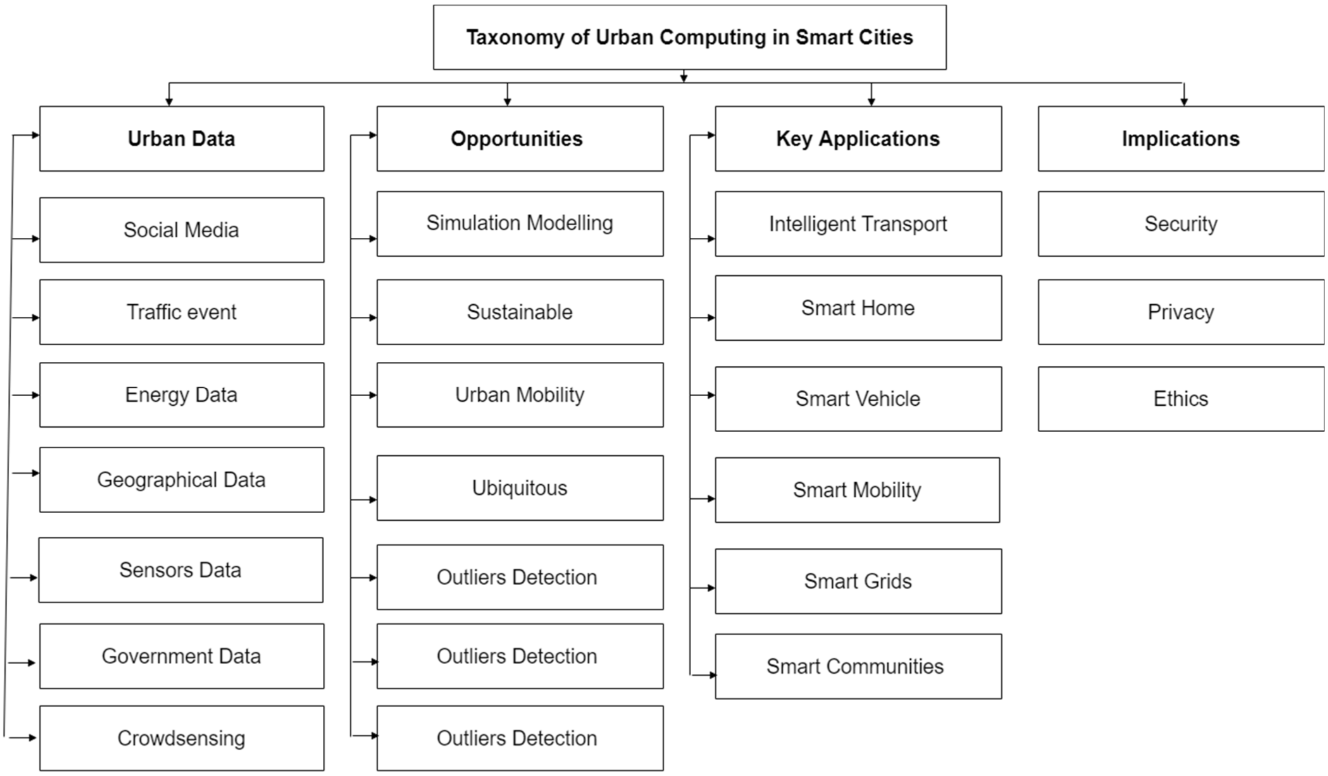

Figure 4. Taxonomy of urban computing in smart cities. https://generaltools.com/toolsmart (accessed on 12 August 2021).

4.1. Urban Data

With the potential increase in the global population, the world is moving fast towards urbanization. According to some studies [53,54] 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 [55,56].

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 [57]. 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 [58]. 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 [59,60]. However, urban computing programs have given residents of smart cities technological and social options. According to [61], 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. Ref. [33] developed a prediction model using the urban data collected from different sources in Aarhus, Denmark. The information gathered relates to city structures, vehicular traffic, air pollution, weather forecasting, and POI. RMSE and MAE were used as performance indicators to evaluate the model based on transfer learning. Moreover, Low et al. [62] propose POI conflation in six stages, namely, standardization of schema, collection of data, mapping of taxonomy, POI matching and unification, and verification of data. The proposal was implemented in a real-world environment in Singapore as a case study. It was found that its practical application indicated the success of the framework for merging five different sources of POI data into unified POI data. The investigation found that the final unified dataset was better than the constituent POI data in terms of comprehensiveness and exhaustiveness.

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 [63]. Ref. [3] propose urban computing for inhalable particulate matter distribution across residential groups in a smart city. A courtyard was built for residential clustering. Simulations were conducted for variants of the type of courtyard for the residential clusters. The various dilutions and atmospheric pollutants were investigated to measure the influence of each. It was found that in terms of fine PM2.5 concentrations in the clusters, the plane courtyard-type layout cluster had the worst performance, while the U-type cluster was the most favourable form. Ref. [64] described a dataset containing information on the actual occupancy and count of five rooms in a university setting, as well as data on indoor ambient criteria, devices enabled by Wi-Fi, consumption of energy by the users, operations of HVAC, and outdoor weather. Among the five rooms were two lecture halls of differing sizes, a support staff office, a research office, and a student-accessible library. Each of the 5 rooms' data were gathered for 181 days with a 5-minute sampling duration. The data were used as a benchmark, for modelling occupant behaviour, as techniques driven by data, and for building simulation. Table 2 provides a comparison of various data sources for urban computing tasks.

Table 2. A comparison of various data sources for urban computing tasks.

Data Source	Content Format	Complexity	Analytical Tools	Application(s)
Social media	Unstructured and semi-structured	High	• Apache Spark • RapidMiner • SAS	• Sentiment analysis • Text analysis • Crime detection • Customer behaviour analytics
Traffic event	Semi-structured	Medium	• Apache Spark • Splunk • HadooSp MapReduce	Predictive analytics
Energy data	Semi-structured	Medium	• Apache Spark • Hadoop MapReduce	Predictive analytics
Geographical data	Unstructured	High	• ArcGIS • BioMedware • R-Analysis of Spatial Data • GeoVista Studio Project	Temporal analytics
Sensor data	Unstructured	High	• Hadoop MapReduce • Apache Spark • Talend	• Predictive analysis • Smart healthcare
Government data	Structured and unstructured	Medium	• Apache Spark • Hadoop MapReduce	Urban planning

4.2. Opportunities

The rapid growth of urban computing technologies for smart cities raises new opportunities for numerous research areas such as simulation modelling, urban mobility, ubiquitous cities and outlier detection, etc. The following subsection offers a brief discussion of some of the opportunities in urban computing for smart cities.

4.2.1. 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 [65–68]. Simulation modelling also comes with some challenges, as a simulation requires an extensive amount of data and computing to be considered an accurate simulation. Another challenge regarding simulation modelling is its inability to adapt to constantly changing data in urban computing applications [69].

4.2.2. Urban Mobility

Urban mobility is regarded as the key to achieving sustainable development goals, and it drives both economic development and social development [70]. 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 [71]. 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 [72–74]. 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 [75].

4.2.3. 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. [76] 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. In a study by [77], a framework is developed, which focuses on the variation in big data sources and improves the computational expense with respect to colossal work. The framework uses a unified strategy to analyse a heterogeneous data stream using geographical and temporal analysis. The study's findings demonstrate the suggested framework's generality, feasibility, and efficacy through various demonstrations of use cases and illustrations derived from the requirements of real-world environments that are collected in various cities. Moreover, in recent years, several projects developed by ToolSmart[1] have contributed to the improvement of smart cities, including Bluetooth Connected Digital Angle Finder, Wi-Fi

Connected Video Inspection Camera, etc. These projects have allowed researchers and practitioners to collect more accurate data.

4.2.4. 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. [78] 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.

4.3. Key Applications

Key applications are crucial aspects of a smart city, contributing to data generation for urban computing. This section briefly discusses some key smart-based applications (see Figure 5) and provides a summary of each application in Table 3.

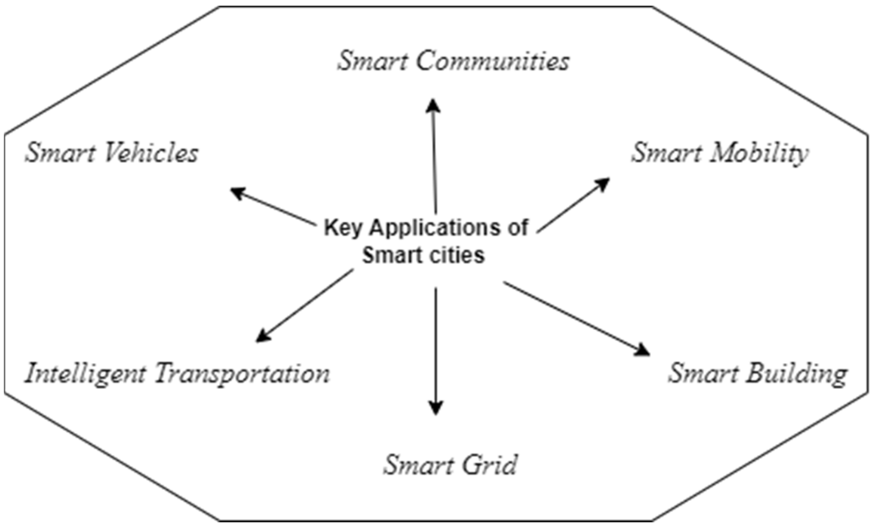

Figure 5. Classification of smart city key applications.

Table 3. A summary of the key applications of a smart city.

Smart City Component	Urban Data	Communication Technologies	Solution(s)	Limitation(s)	Ref.
Intelligent transportation	- Traffic flow sensor data - Log files - GPS location data - Sensor data	Wi-Fi and ZigBee	- Traffic and mobility management - Route information - Safety and vehicle control (it enables drivers and also warns them about their driving proficiencies, road conditions, and vehicle performance) and electronic timetable	- Lack of travel behaviour modelling - Detection of obstacles for moving cameras and moving objects	[79–81]

Table 3. *Cont.*

Smart City Component	Urban Data	Communication Technologies	Solution(s)	Limitation(s)	Ref.
Smart home	Sensor data	Wi-Fi	- Intelligent monitoring - Remote control - Cyber-physical system	- Not fully connected to various service providers to automate and optimise services - User privacy violations	[82–85]
Smart vehicles	Sensor data	WiMAX and Bluetooth	Optimising flow of vehicles, reducing the frequency of traffic jams and accidents	- Maintenance costs	[86]
Smart mobility	Sensor data	Bluetooth and 5G mobile devices	- Routes based on the user's preferences - Pedestrian movement tracking	- Design appropriate behaviour modelling	[87]
Smart grid	Sensor data	WiMAX and ZigBee	- Advanced metering infrastructure (AMI) - Home energy management system (HEMS)	- Cyber physical attacks - Communication delays	[88–90]
Smart communities	User data Sensor data	Wi-Fi	Improve nation's income in the following areas: economic diversity and growth, energy efficiency and climate change mitigation, efficient transportation and mobility, and community resilience and safety	Scalability	[91–93]

Intelligent Transportation: Intelligent transport systems (ITSs) are among the major components of any urban computing smart city [94]. 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) [79]. 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 [95]. 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.) [96]. 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 [97].

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 [98]. 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 [99]. A cyber-physical system (CPS) is a typical illustration of a smart building [84,100] 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 [83]. Given below is a brief summary of the recent studies concerning smart buildings.

(i) HVAC and plug load controls in Smart Buildings: [101] examined how to use minimum sensing strategies to predict occupancy in different types of spaces (offices, libraries, and lecture rooms) using data from a variety of sensors that measure indoor and outdoor environmental conditions, Wi-Fi device connections, consumption of energy, operations of the HVAC system, and data related to time. Bi-GRU, DNN, Bi-LSTM, GRU, and LSTM were utilized to produce the predictions. A novel feature selection approach was used to find the essential attributes for predicting occupancy. The outcomes demonstrated that the algorithm used for the feature selection outperformed the compared algorithms (RFECV). Using Bi-GRU in offices, GRU in libraries, and Bi-GRU in lecture rooms yielded the best model performance. Ref. [101] indicated that building managers and researchers might use the insights gathered to determine the most significant variables for occupancy prediction and decrease the requirement for costly sensors. To increase the generalization of the findings, the research could be extended in the future to include different sorts of venues. Ref. [102] introduced a new Access Control and Delegation (ACD) method that employs the eXtensible Access Control Markup Language (XACML) to protect access to MQTT topics in Internet of Things (IoT)-based emergency management systems. The suggested mechanism incorporates a new decision point referred to as the delegation decision point (DDP), which examines delegation control policies utilizing new rule- and policy-combining algorithms. The evaluation procedure analyses the delegation method's validity, depth, and quantity of delegates. The ACD mechanism was deployed in a testbed. The outcome demonstrated that the proposal is effective and that the evaluation of the DDP latency was ideal for IoT systems. Plug-Mate is an Internet of Things (IoT)-based technology that aims to reduce energy consumption and expenditures by turning off plug loads in empty rooms.

(ii) Management of Emergencies in Smart Buildings: [101] created a Plug-Mate system to regulate the energy consumption of plugged-in devices in smart buildings. The system consists of occupancy sensors, smart outlets, and a central hub that collects occupancy data and tells smart outlets to switch on or off plug loads as necessary. The system is made easy to install and scalable and can be maintained and controlled via a smartphone application. The proposed system automates plug loads based on user input using a network of connected modules and three subsystems. First, a non-intrusive indoor localization system collects high-resolution occupancy data; then, plug load type data are deduced via a sophisticated plug-load identification function; and finally, a variety of control options are presented via a proprietary user interface. In addition, the report indicates that Plug-Mate has been tested and demonstrated in a pilot study.

(iii) Occupancy detection in Intelligent Buildings: [103] proposed the use of short-term occupancy prediction algorithms for HVAC system control in energy-efficient buildings. These algorithms, which anticipate when a room or space will be used and manage the HVAC system accordingly, are intended to boost the energy efficiency of buildings.

The three-step procedure begins with an identification-based technique employing the Expectation Maximization (EM) algorithm for model identification. Then, utilizing a general systems problem solver (GSPS), a novel finite-state automaton was investigated (FSA). In the final step, a fuzzy-based stochastic basis role was provided. The research demonstrates that data collected from occupancy sensors and other sources can be used to train occupancy prediction systems using machine learning techniques. The paper also discusses the benefits of using occupancy prediction algorithms for HVAC control, such as increased energy efficiency, occupant comfort, and cost savings. The adoption of these algorithms has the potential to significantly reduce energy consumption in buildings, according to the conclusion of the article.

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 [104]. 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 [105], 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 [106]. Smart vehicles are implemented using IEEE 802.11.p and IEEE 1609 standards [107] 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 [108]. Moreover, smart cities gather data from several nodes using various electrical devices and sensors. Other infrastructures can communicate with transport systems within the environment [108,109].

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 [110]. 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 [111,112]. An intelligent mobility approach is required to guide and support inhabitants living in smart cities [113]. 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 [87].

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 [114]). The tremendous energy demand in smart cities has ushered in the SG evolution [115]. 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 [116]. 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 [90]. The general packet radio service is an SG communication technology used for long-distance data transfer over a circuit switch [117]. 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 [118]. 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 [84].

Smart Communities: Smart communities are the basic components of a city [119] 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 [91]. 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 [92] 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 [120]. Furthermore, smart communities can support and improve a nation's income through diversification of the economy, energy, climate, transportation and mobility, and security [91,92].

4.4. Implications

Recently, many studies have focused on frameworks, methods, and algorithms for securing network communications, smart applications, and the privacy of data collected from various sources in a smart city. In this section, we briefly discuss some of the technical challenges and the possible solutions proposed in the existing works based on security, privacy, and ethics. Table 4 illustrates some examples of the implication guidelines.

Table 4. A summary of the security, privacy, and ethics guidelines.

Implications	Guidelines
Security [121,122].	• Authentication capabilities • Automatic and secure updating of software • Dealing with virtualisation vulnerability
Privacy [123,124].	• Laws and regulations on how data are governed • Data locations should be made available to users • Enabling bases for trust and privacy on data in an organization requires the establishment of ownership rights
Ethics [125,126].	• Awareness of users to share data on mobility • Establishing transparency for collectors of urban data and for users • Deviate from biases of data sources and collection procedures

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 [127,128]. 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 [129]. 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 [129]. 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 [130]. For Wi-Fi, the main components are radio communication and transmitters and receivers of Wi-Fi, which enhance guest access, increase mobility, allow network expansion, and support collaboration. Wi-Fi is vulnerable to the following threats: rogue access points, malicious phishing, improper configuration, unauthorized access to a system, loss of signal because of DoS, war dialling, tunnelling of protocol, MitM, and DDoS/Dos attacks [79]. LTE provides new features, such as a high bandwidth that supports urban computing in terms of cost optimisation, computational time, and low energy consumption [131]. The security issues in 4G LTE, LTE-A, and 5G networks are DDos/Dos attacks, phishing attacks, and identity attacks [132].

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. [133], 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 [133]. For instance, managing the traffic system has become an issue in transportation systems due to the nature of connected vehicles. Moreover, citizens' demands in terms of the provision of fast transportation will also increase, which may lead to privacy breaches of users' data during communication [94]. This, in turn, will make users lose confidence in such a system. Therefore, it is imperative to use strong cryptography tools to secure devices used during communication to preserve individuals' privacy in the presence of adversaries [134,135].

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 [136]. 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 [136]. Personal privacy has complex phases [137].

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 [138]. However, privacy is the major prerequisite for autonomy [136,138].

5. Prominent Use Cases of Urban Computing in Smart Cities

This section presents different use cases of urban computing in smart cities. The main aim is to show how urban computing is used in a smart city. Some of the use cases of urban computing in smart cities are in planning, urban computing for the environment, urban computing for transportation systems, urban computing for smart cities, energy consumption, and urban computing for smart cities' economies. The detailed discussions are presented as follows:

- **Urban computing for smart cities:** To build an intelligent city, effective planning is imperative. One of the most important application domains in urban computing is smart city planning. With the advancement of human civilisation, the need for smart city planning that can incorporate transportation and land use planning cannot be overestimated, so as to aid the development of social environments and the economy of the society. Moreover, urbanisation is growing rapidly in many developing countries; therefore, the need for new technologies that can remotely understand urban changes and give key data for a smart city's maintainability is very important.
- In most cases, carrying out smart city planning requires the evaluation of many factors, such as human mobility, traffic flow, and road network structures. These factors are highly complex and evolve fast; hence, this makes smart city planning a very challenging task. For instance, in order to understand urban travelling designs, a few research works were conducted based on travel assessment information [139,140].

Hereafter, finding useful areas in a city is very important. Useful areas such as business districts and educational support for various requirements of people's urban lives stand as key techniques for shaping and outlining comprehensive information about an urban city. Therefore, understanding key useful areas in a given city can standardise urban planning, further fast-tracking other things, such as choosing a location for business purposes. In a study by Yuan, Zheng et al. [141], the authors proposed a new framework named DRoF. This framework identifies areas of diverse roles in an urban city by utilising people's movements between areas and POIs in a given region. In another study by Sheng, Zheng et al. [142], the authors also explored some useful areas with a related distribution of POIs in a given region.

- **Urban computing for the environment in smart cities:** Cities are currently facing multitudes of problems that result in huge challenges. For example, in several developing countries, air pollution is a big issue and a great concern. In most of these countries, governments have constructed a relative number of air quality monitoring stations in cities to notify individuals of the amount of pollution in the air in a given area. However, urban air quality is very lopsided in cities that depend on multiple complex factors such as meteorology, land use, and traffic volume. Therefore, building many monitoring stations can be highly expensive with regard to human resources, land use, and money. Hence, people will not identify the air quality if a city is devoid of monitoring stations. Zheng, Liu et al. [143] proposed a cloud-based system that deduces real-time information on air quality in a city based on reported historic and instantaneous air quality information. In a study by Becker, Caceres et al. [144], the authors retrieved information from cellular calls to comprehend city aspects that brought on people's movements. Furthermore, another study by [145] proposed the handling of outbound phone calls to illustrate people's movements. Later, a study was conducted to extract data on mobility from hints of phones [146]. The other form of pollution affecting people in smart cities is noise. This kind of pollution can result in physical and mental health problems for people. The initial step in understanding urban noise is to measure the noise level in a city. In a study by Liu, Zheng et al. [147], the researchers proposed two methods for measuring urban noise levels. In other case studies [148,149], the studies are based on mobile-phone-based approaches that explore the noise state in New York City. Furthermore, in a study by Martí, Rodríguez et al. [150], the authors proposed a mobile application to determine noise contamination with the participation of citizens. Several countries such as the USA, the UK, and Germany are monitoring noise pollution. These countries utilise noise maps to access noise pollution levels. The noise maps are computed using simulations that are reliant on inputs, such as vehicle type, road type, and traffic flow data. Because collecting such information is highly expensive, these maps can be updated only after a long period of time. In the study by Santini, Ostermaier et al. [151], the authors obtained noise pollution data in urban areas with the utilisation of wireless sensor networks. However, deploying such technology in big cities can be very expensive with respect to both finances and human resources.
- Urban computing for energy consumption in smart cities: Rapid urbanisation and the development of smart cities are consuming a vast amount of energy [152]. Hence, obtaining technologies that can sense city-scale energy costs, increase energy infrastructures, and also decrease the amount of energy consumption is critical. We have two forms of energy consumption in urban cities: gas energy consumption and electrical energy consumption. Concerning gas consumption, a study by [153] proposed a method to aid in the instantaneous detection of refuelling behaviour of people and of whole citywide petrol intake. This method analyses and draws interpretations from GPS routes that are passively retrieved by cabs. Ref. [154] infer the gas intake and pollution discharge of automobiles commuting on a city road network utilising GPS technology from a section of automobiles. The results show that given a road's traffic volume and travel speed, the gas intake and discharge can be determined based on

the current environment. With regard to electricity consumption, to enhance domestic energy consumption, an effective combination of energy from renewable sources to meet the increasing request via electric vehicles is key to sustainability. Smart algorithms employed at the technology level or communal level will help in staying within a community-assigned energy intake level. In a study by [155], the authors make sure that each automobile within a community is organised using a strengthening learning agent, which a temporary load prediction algorithm will additionally sustain. In another study, [156] proposed a new framework that will help in supporting charging and storage structure design for electric vehicles.

- Urban computing for transportation in smart cities: Concerning urban computing for transportation in smart cities, the pillar of city life is transportation. However, transportation authorities normally have no instantaneous outlook on traffic position. Hence, the huge dependency on petroleum along with the environmental effects of discharges from fossil fuel intake make the energy intake of urban transportation in smart cities a challenging issue to overcome. Furthermore, the key part of a transportation system is the refuelling behaviour of vehicles by individuals. Hence, a method for identifying global information in an instantaneous manner is proposed by Zhang, Wilkie et al. [153]. In Montreal [157], websites are integrated with LTE to provide a voluminous machine-to-machine (M2M) model for traffic. The model has the capacity to determine the position of smart meters, traffic lights, and smart bus stops. It allows the analytics of traffic data collected from the M2M model.
- Urban computing for government policy in smart cities: Urban computing plays a role in new government policy, such that the introduction of new government policy in smart cities can come with anxiety/panic in citizens living in the smart cities because of fear of the unknown or uncertainty about the impact of the new policy on the citizens. Governments can leverage urban computing to understand the likely acceptability of a new policy by citizens. If the urban computing output indicates the acceptability of the policy, the government can go ahead to implement the policy. If it shows a lack of awareness of the new policy, decision-makers can make tremendous efforts in creating awareness about the new policy. In case of rejection of the policy by citizens, additional work can be conducted based on urban computing to gain insight into the likely reasons for rejection of the new policy for future improvement or modification of the policy in order to better serve the citizens in the smart city. City governments gather data through various collection strategies, such as smart sensing, crowd sensing, crowdsourcing, opportunistic sensing, and unobtrusive continuous sensing. This massive big data collection facilitates the implementation of city-wide day-to-day operational intelligence to improve citizens' lifestyles, city operations, and city environments [12]. In addition, real-time analytics help city governments control crime, respond to emergencies, and handle chaotic situations, such as riots, massive traffic jams, and viral diseases.
- Urban computing for business processes in smart cities: The services provided by a smart city to citizens through various city systems are facilitated via urban computing. Hence, the objectives of urban computing should be aligned with the business processes across city systems, and the primary prerequisite for city system integration for smart city development (SCD) is business process change (BPC). The best practices for enterprise systems integration (ESI) have been recognised and implemented since the 1940s. Javidroozi et al. [158] focused on understanding the similarities between SCD and ESI. The study provided a comparison framework highlighting that ESI could be utilised to address BPC challenges in an SCD context. The proposed framework will help researchers to focus on the social and technical aspects of city system integration.

6. Open Research Challenges

The involvement of urban computing in performing diverse and complex task execution poses several challenges for realising the vision of smart cities. This section discusses the main challenges and brings forward some guidelines to solve the identified challenges.

6.1. Cognitive Cybersecurity

Despite the successful development recorded in cyber security big data analytics, many issues remain unresolved. Current research reveals that most of the existing analytic techniques do not emphasise the reasoning to "understand" cyber security threats and risk, which causes inefficient threat detection. Therefore, researchers are currently focusing on the optimisation of the techniques for handling big data analytics issues. Big data encompass voluminous amounts of data generated at high speed for management in repositories that are distributed remotely. As a result of that, researchers were prompted to propose powerful advanced technology for effective and efficient analytics of large-scale data. The analytics for big data help governmental and non-governmental organizations to find new knowledge hiding in the voluminous data, such as people's behaviour towards a certain policy or healthcare predictive models for use by departments of health. The application of cognition for detecting security threads in such voluminous data is required to be developed for the improvement of businesses and security. Cognitive analytics has the potential to solve the limitations of human cognition by processing and understanding big data for cyber security in real time.

6.2. Air Quality

Poor air quality in a major urban city is considered a critical environmental issue, and real-time air pollution data collection and analysis in a smart city is essential for urban sustainability. The construction and maintenance costs needed for air pollution stations are too high. Hence, cost-effective means are needed to measure air pollution. Ref. [53] proposed a predictive model, which uses urban data from heterogeneous sources to predict particulate matter. The proposed model used the concept of transfer learning, and the results show that the proposed model is superior to all baselines. Moreover, social media data and social events are also discussed as a future extension to improve the accuracy of the proposed model.

There are various open research challenges in the field of air quality. The primary challenge is the quantification and prediction of the health impacts of air quality. Researchers have undertaken considerable work on quantifying the impact of air quality on human health, but it remains a challenge due to climate change's impact on air quality [159,160]. The prediction of the health impacts of air pollution, including hospitalisations and mortality, has also been studied [161], but researchers recommend future designs to better serve decision-making [162]. Researchers also recommend location-specific studies to eliminate the risk of exposure misclassification, which is argued against due to aggregated exposure from point, non-point, and mobile sources [163].

Another open challenge regarding air quality is building sustainable solutions that can mitigate air quality and that are financially viable. Sustainable solutions can be achieved via further improvements in satellite-based remote sensing and fusing the related data to accurately resolve PM2.5 concentrations in a wide range of conditions [164]. The infrastructure costs to mitigate air quality degradation due to combustion sources in cities and urban areas are daunting in an economic sense [165], but various types of research have shown that the benefits of better air quality, especially regarding CO2, offset the cost of climate policy implementation [166].

6.3. IoT Resources

With the growth in electric vehicles (EVs), the ways people transit are changing. There are various factors that affect EV performance and the environment, which include energy efficiency, durability, and so on. However, with the utilization of EVs comes the challenge of moving EV data and connecting them to the cloud. Hence, these big data collected from EVs create an opportunity for researchers to develop new and novel approaches for the exchange and transportation of information. In a study by Lee et al., to resolve this issue, the researchers proposed an energy management scheme whereby EV system data were utilized to understand patterns for long-term performance estimation using big data [167]. The results show that the proposed scheme can successfully help in moving big data from EVs to the cloud and aid in analysing drivers' behaviours and driving range. In another work by Galus et al. [168], the researchers also worked on ways to manage data collected from plus-in hybrid electric vehicles (PHEVs. The smart management of data extracted from PHEVs can help to reduce or eliminate potential congestion in power systems and to distribute available energy efficiently. The authors proposed a new scheme that incorporates price dependability for the analysis of PHEV integration and data management possibilities. Ref. [169] conducted a comprehensive study on big data movement. The authors outlined some of the challenges in data processing. Firstly, the authors outlined new database architectures that support big data storage and processing. Secondly, big data issues such as data sources, processing, and analysis were discussed. Hence, the authors showed how the parallelization of bug data during processing can be used by programmers not only in a distributed way but also within each server.

The results showed that the energy consumption by the proposed framework is significantly less than the energy consumed by transfer over the internet. The proposed framework sets a platform to reduce the delay of data transfer in smart cities and provides researchers with a benchmark to explore hybrid techniques, whereby data transfer is achieved by both vehicles and the internet. It is well known that the collection and maintenance of voluminous data from various sources in a smart city is a challenge. In addition, the transmission of the data to units of control for analytics and processing is posing a challenge. To help smooth the transmission of data effectively, [170] proposed an approach for the reduction of energy consumption and carbon emission. The proposed approach was able to speed up data transmission. Similarly, Rashmi et al. propose the Internet of Buses (IoB) as a subset of the Internet of Vehicles (IoV). The initiative enables buses for public transportation as a service for data carriers [171]. Despite the development, a lot of future research is required to develop this area.

6.4. Cyber-Physical System

The large-scale arrangement of cyber-physical systems challenges sequence issues in different areas that require further smart sensing and computing techniques, including advanced networking and communications tools, in order to offer more pervasive cyber-physical services. The difficulty to convert classical cities that were built haphazardly due to overpopulation and ill planning into smart cities is the infrastructural challenge to smart cities related to urban computing. Countries with large demographics and diversity present great challenges and opportunities, and the new technologies in smart cities need to provide sustainable solutions and civic amenities for urban populations and citizens. There are some instrumentation challenges related to urbanisation such as environmental pollution, transportation management, energy usage, and public health [172].

According to a recent study in 2022 [173]), cyber-physical systems will continue to grow using and needing several forms, and smart cities are one of the methods highlighted by the authors. The speedily moving landscapes of urban movement in a smart city will deliver movement solutions that provide sustainable use. Cyber-physical systems have developed into very complicated systems with miscellaneous methods for data streams, handling a huge amount of data and supplying a wide range of services [174]. Currently, various researchers, management decision-makers, technical staff, and industrial specialists are working towards cyber-physical systems on account of the development of various applications in international guidelines and critical infrastructures for smart city advances [175]. Therefore, cyber-physical systems play an important role in different applications, particularly those utilizing network and physical devices.

6.5. Data Sparsity Problem

As a result of generating data from diverse sources within an urban city, there is the challenge of data sources with few and scattered data within the urban city. This poses a challenge to the urban computing ecosystems in smart cities. The best way to integrate these sparse data from diverse sources for effective urban computing remains an open problem [176]. We suggest the integration of models for handling the data sparsity problem into the urban computing ecosystem in a smart city. Moreover, Greenland, Mansournia, and Altman [177] highlighted the factors contributing to sparse data bias, including narrowly distributed continuous predictors, low event per variable, and categorical covariates with very low or high prevalence.

6.6. Data Movement

Smart cities are supposed to manage IoT resources and their data efficiently. Nevertheless, if the number of IoT devices is enormous, this will lead to issues in the acquisition, transfer, and analysis of big data. The traditional networks that transfer data are costly in terms of energy consumption and delay. Ref. [178] proposed a volunteer vehicles-based data transfer framework that can promote social awareness and energy conservation. The proposed framework sets a platform to reduce the delay of data transfer in smart cities and provides the researchers with a benchmark to explore hybrid techniques, whereby data transfer is achieved by both vehicles and the internet. The results showed that the energy consumption by the proposed framework is significantly less than the energy consumed by transfer over the internet.

6.7. (5G) Technologies

As the deployment of 5G technologies is spreading fast across global urban cities because infrastructure and resources are mostly concentrated in urban cities [179], this has implications for urban computing in the aspect of data analytics. Although the advent of 5G technologies has brought improved services to the telecommunication industry, it has also brought new challenges to the research community. The advent of 5G technologies has tremendously improved the speed of communication and the generation of very high volumes of data at very high speeds never witnessed in the era of 4G and below. The rate at which data are generated from heterogeneous sources [180] in an urban city is a concern to the urban computing community because the data need to be collected and processed to gain insight and valuable information and acquire new knowledge. With the rate at which data are generated via 5G technology heterogeneous sources, hardware for data storage will shortly become a serious challenge to the industry and academia. On the other hand, the high volume of data being generated and collected has made shallow algorithms lack the capability to process them because it is known that shallow machine learning algorithms operate very well with small samples of data, such that as the volume of the data increases, the efficiency and effectiveness of the shallow algorithm reduce. Though some special hardware for processing high volumes of data using deep learning algorithms have started springing up, we believe that special hardware to support the processing of high-volume data using a deep learning architecture should be the new focus, and, as the central collection of data might not be feasible in the future, we recommend the adoption of federated learning for data analytics in urban computing.

The 5G deployed for urban computing has security threads. Security threads for 5G technology inter-slicing handover are highly challenging because the security threads are dynamic as a result of different technology embodiments in the environment. The security vulnerabilities in the inter-slice are brought about by the embodiments of different technologies including, but not limited to, network functions virtualization, machine learning, software-defined network, and the IoT, each exposing its security vulnerabilities in the network inter-slicing [181]. Deploying 5G technologies in urban computing could expose urban computing to different forms of security attacks launched by attackers exploring the security weaknesses of the 5G technologies in the network inter-slicing handover. The possible attacks that can be carried out in 5G inter-slicing in urban computing are as follows, as enumerated in Sajjad et al. [181]: session hijacking, redirection attack, denial-of-service, malicious mobile node flooding, and man-in-the-middle attacks. We recommend that the research community develop a machine learning robust cybersecurity defence system for inter-slice handover protection against attacks in urban computing with the capability to handle dynamics in the inter-slice handover security threads.

6.8. Scaling via the Analysis and Harvesting of Energy

The powering of the pervasive computing devices embedded in the environment requires massive amounts of energy. As of today, batteries are required for the charging of pervasive computing devices. In the future, operation will be required to continue for months or years without the need for changing batteries because it is not feasible to continue replacing batteries. Therefore, limited battery capacity can pose a challenge. Other scaling methods include the effect of pervasive computing at scale on human factors, scalable pervasive computing scaling support, and the theoretical foundations of pervasive computing scaling [182,183]. Furthermore, pervasive computing through sensors and mobile phones can be challenged with the issue of storage and power. Therefore, to resolve the issue of storage and power, cloud computing is put forward as an alternative solution. Cloud accessibility, mobile clouds, networks in the cloud, and clouds and crowds are part of the cloud solution.

6.9. Knowledge versus Privacy

It is no wonder that there is a problematic of balancing privacy and knowledge. It is believed that a smart system is potentially more intelligent with more information on a person [184]. The decisions on trade-offs should be controlled by the individuals concerned in sustainable smart cities. They should be able to choose for what purpose and for how long such data should subsequently be accessible and available in the system. The challenge now is to find the right balance that requires transparency about the data that are truly required to deliver smart services. This is also consistent with that which has been in effect since May 2018 under the EU-GDPR [185]. At present, people have no choice but to decide between knowledge and privacy but are faced with severe privacy breaches [186,187]. Furthermore, humans are progressively being removed from operating, supervising or, at the very least, being in charge and thus from being in control due to pervasive and mobile intelligence [188]. Three problematic areas categorise problem areas induced by smart cities. First, rigid behaviour can be experienced by users and customers faced with online shops or fully automated call centres without the involvement of human operators [189]. Only small deviations from the standard routine or process are needed, and the system cannot handle requests. Secondly, despite ubiquitous promises, the weakness and error-prone conduct of AI and other algorithmic approaches can be observed today in many areas, and, lastly, lack of transparency, traceability, and accountability are imminent problems of artificial intelligence and the most important question of the 'smart-all' paradigm [188].

6.10. Intersection of Smart and Sustainable City

The challenges of the intersection between smart cities and sustainability are identified as follows: the overemphasis on the applications of technology, the complexity of the initiative in practice, and the smart city conceptualization are ad hoc in nature. To mitigate these challenges, a solution is proposed by presenting new indicators for the intersection of smart cities and sustainability cutting across the economy, the socio-cultural landscape, the environment, and governance [190]. However, the solution is theoretical in nature without a practical solution, which makes it remain abstract. We recommend researchers, industry practitioners, and academia to develop a practical model for a smart sustainable community to assess the feasibility of its practical application in the real world.

7. Conclusions

The incredible miniaturisation of sensors and communication technologies in urban spaces has led to the development of new technological ecosystems for smart cities. Urban computing aims to bring improvements to citizens' lifestyles and city environments and to enrich operational intelligence in smart city services. In this article, we investigated, highlighted, and reported state-of-the-art efforts directed towards the smart city paradigm in urban computing. We presented numerous applications and technologies to qualitatively analyse the role of urban computing in smart cities. We outlined four prominent use cases of urban computing in smart cities. Furthermore, several future research challenges were enumerated. Finally, we conclude that although urban computing can provide many benefits in smart cities, the convergence of these paradigms engenders some new research challenges that need to be addressed in the future.

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References

1. Koliopoulos, T.; Kouloumbis, P. Urban Computing and Smart Cities: Web Utilities Characteristics that Support Sustainable Smart Cities. In *Resilient and Responsible Smart Cities*; Springer: Cham, Switzerland, 2022; pp. 115–124.
2. Zheng, Y. Unified Urban Governance Models. *J. Wuhan Univ. Inf. Sci. Ed.* **2022**, *47*, 19–25.
3. Ma, X.N.; Zhao, J.; Guo, P. The urban computing on the distribution of inhalable particulate matters to Smart City–based residential groups. *Concurr. Comput. Pract. Exp.* **2019**, *31*, e4803. [CrossRef]
4. Bibri, S.E. Data-driven smart sustainable cities of the future: Urban computing and intelligence for strategic, short-term, and joined-up planning. *Comput. Urban Sci.* **2021**, *1*, 8. [CrossRef]
5. Silva, B.N.; Khan, M.; Han, K. Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities. *Sustain. Cities Soc.* **2018**, *38*, 697–713. [CrossRef]
6. Bouroche, M.; Dusparic, I. Urban computing: The technological framework for smart cities. In *Handbook of Smart Cities*; Springer: Cham, Switzerland, 2021; pp. 89–112.
7. Cheng, B.; Fan, C.; Fu, H.; Huang, J.; Chen, H.; Luo, X. Measuring and Computing Cognitive Statuses of construction Workers based on Electroencephalogram: A critical review. *IEEE Trans. Comput. Soc. Syst.* **2022**, *9*, 1644–1659. [CrossRef]
8. de Oliveira Cavalcanti, C.; Limont, M.; Dziedzic, M.; Fernandes, V. Sustainability assessment methodology of urban mobility projects. *Land Use Policy* **2017**, *60*, 334–342. [CrossRef]
9. Bibri, S.E.; Krogstie, J. Smart sustainable cities of the future: An extensive interdisciplinary literature review. *Sustain. Cities Soc.* **2017**, *31*, 183–212. [CrossRef]
10. Zeng, X.; Yu, Y.; Yang, S.; Lv, Y.; Sarker, M.N.I. Urban resilience for urban sustainability: Concepts, dimensions, and perspectives. *Sustainability* **2022**, *14*, 2481. [CrossRef]
11. Chatterjee, S.; Kar, A.K.; Gupta, M.P. Success of IoT in smart cities of India: An empirical analysis. *Gov. Inf. Q.* **2018**, *35*, 349–361. [CrossRef]

12. Zheng, Y.; Capra, L.; Wolfson, O.; Yang, H. Urban computing: Concepts, methodologies, and applications. *ACM Trans. Intell. Syst. Technol. (TIST)* **2014**, *5*, 1–55. [CrossRef]
13. Kashef, M.; Visvizi, A.; Troisi, O. Smart city as a smart service system: Human-computer interaction and smart city surveillance systems. *Comput. Hum. Behav.* **2021**, *124*, 106923. [CrossRef]
14. Hefnawy, A.; Bouras, A.; Cherifi, C. Iot for smart city services: Lifecycle approach. In Proceedings of the International Conference on Internet of things and Cloud Computing, Dalian, China, 22–23 October 2016.
15. Liu, J.; Li, T.; Xie, P.; Du, S.; Teng, F.; Yang, X. Urban big data fusion based on deep learning: An overview. *Inf. Fusion* **2020**, *53*, 123–133. [CrossRef]
16. Kamal, M.; Atif, M.; Mujahid, H.; Shanableh, T.; Al-Ali, A.R.; Al Nabulsi, A. IoT based smart city bus stops. *Future Internet* **2019**, *11*, 227. [CrossRef]
17. Sangaiah, A.K.; Dhanaraj, J.S.A.; Mohandas, P.; Castiglione, A. Cognitive IoT system with intelligence techniques in sustainable computing environment. *Comput. Commun.* **2020**, *154*, 347–360. [CrossRef]
18. Janssen, M.; Luthra, S.; Mangla, S.; Rana, N.P.; Dwivedi, Y.K. Challenges for adopting and implementing IoT in smart cities. *Internet Res.* **2019**, *29*, 1589–1616. [CrossRef]
19. Al-Turjman, F. 5G-enabled devices and smart-spaces in social-IoT: An overview. *Future Gener. Comput. Syst.* **2019**, *92*, 732–744. [CrossRef]
20. Amanullah, M.A.; Habeeb, R.A.A.; Nasaruddin, F.H.; Gani, A.; Ahmed, E.; Nainar, A.S.M.; Akim, N.M.; Imran, M. Deep learning and big data technologies for IoT security. *Comput. Commun.* **2020**, *151*, 495–517. [CrossRef]
21. Liu, Y.; Dai, H.N.; Wang, Q.; Shukla, M.K.; Imran, M. Unmanned aerial vehicle for internet of everything: Opportunities and challenges. *Comput. Commun.* **2020**, *155*, 66–83. [CrossRef]
22. Niu, X.; Zhu, Y.; Zhang, X. DeepSense: A novel learning mechanism for traffic prediction with taxi GPS traces. In Proceedings of the 2014 IEEE Global Communications Conference, Sydney, Australia, 10–14 June 2014.
23. Assem, H.; Ghariba, S.; Makrai, G.; Johnston, P.; Gill, L.; Pilla, F. Urban water flow and water level prediction based on deep learning. In *Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2017, Skopje, Macedonia, 18–22 September 2017*; Springer International Publishing: New York, NY, USA, 2017.
24. Banerjee, P.S.; Mandal, S.N.; De, D.; Maiti, B. RL-sleep: Temperature adaptive sleep scheduling using reinforcement learning for sustainable connectivity in wireless sensor networks. *Sustain. Comput. Inform. Syst.* **2020**, *26*, 100380. [CrossRef]
25. Najafabadi, M.M.; Villanustre, F.; Khoshgoftaar, T.M.; Seliya, N.; Wald, R.; Muharemagic, E. Deep learning applications and challenges in big data analytics. *J. Big Data* **2015**, *2*, 1. [CrossRef]
26. Jiang, Y.; Le, B.D.; Zia, T.; Gauravaram, P. Privacy Concerns Raised by Pervasive User Data Collection from Cyberspace and Their Countermeasures. *arXiv* **2022**, arXiv:2202.04313.
27. Usman, A.B.; Gutierrez, J. Toward trust based protocols in a pervasive and mobile computing environment: A survey. *Ad Hoc Netw.* **2018**, *81*, 143–159. [CrossRef]
28. Shaheed, S.M.; Abbas, J.; Shabbir, A.; Khalid, F. Solving the Challenges of Pervasive Computing. *J. Comput. Commun.* **2015**, *3*, 41. [CrossRef]
29. Courant, M.; Lüthi, A. Pervasive Computing and Sustainable Development: A case study in Mobility Management. *Update* **2004**, *2*, 1.
30. Bogomolov, A.; Lepri, B.; Ferron, M.; Pianesi, F.; Pentland, A.S. Pervasive stress recognition for sustainable living. In Proceedings of the 2014 IEEE International Conference on Pervasive Computing and Communication Workshops (PERCOM WORKSHOPS), Budapest, Hungary, 24–28 March 2014; pp. 345–350.
31. Wu, M.; Yan, B.; Huang, Y.; Sarker, M.N.I. Big Data-Driven Urban Management: Potential for Urban Sustainability. *Land* **2011**, *11*, 680. [CrossRef]
32. Bibri, S.E. The IoT for smart sustainable cities of the future: An analytical framework for sensor-based big data applications for environmental sustainability. *Sustain. Cities Soc.* **2018**, *38*, 230–253. [CrossRef]
33. Honarvar, A.R.; Sami, A. Multi-source dataset for urban computing in a Smart City. *Data Brief* **2019**, *22*, 222–226. [CrossRef]
34. Dhirani, L.L.; Newe, T.; Nizamani, S. Hybrid Multi-Cloud Demystifying SLAs for Smart City Enterprises Using IoT Applications. In *IoT Architectures, Models, and Platforms for Smart City Applications*; IGI Global: Hershey, PA, USA, 2020; pp. 52–67.
35. Kakderi, C.; Komninos, N.; Tsarchopoulos, P. Smart cities and cloud computing: Lessons from the STORM CLOUDS experiment. *J. Smart Cities* **2019**, *1*, 4–13. [CrossRef]
36. Yaqoob, I.; Khan, L.U.; Kazmi, S.A.; Imran, M.; Guizani, N.; Hong, C.S. Autonomous Driving Cars in Smart Cities: Recent Advances, Requirements, and Challenges. *IEEE Netw.* **2019**, *34*, 174–181. [CrossRef]
37. Goldberg, M.; Zhang, Z. A cyber-physical system framework towards smart city and urban computing to aid people with disabilities. In Proceedings of the 2018 27th Wireless and Optical Communication Conference (WOCC), Hualien, Taiwan, 30 April–1 May 2018.
38. Xie, S.; Zheng, Z.; Chen, W.; Wu, J.; Dai, H.N.; Imran, M. Blockchain for cloud exchange: A survey. *Comput. Electr. Eng.* **2020**, *81*, 106526. [CrossRef]
39. Zheng, Z.; Xie, S.; Dai, H.N.; Chen, X.; Wang, H. Blockchain challenges and opportunities: A survey. *Int. J. Web Grid Serv.* **2018**, *14*, 352–375. [CrossRef]

40. Ahram, T.; Sargolzaei, A.; Sargolzaei, S.; Daniels, J.; Amaba, B. Blockchain technology innovations. In Proceedings of the 2017 IEEE Technology & Engineering Management Conference (TEMSCON), Santa Clara, CA, USA, 8–10 June 2017.
41. Krishna, G.J.; Ravi, V.; Reddy, B.V.; Zaheeruddin, M. Smart Blockchain: A Formidable Combination of Analytics and Blockchain–A Survey. In *Smart Systems Design, Applications, and Challenges*; IGI Global: Hershey, PA, USA, 2020; pp. 43–62.
42. Rahman, M.A.; Rashid, M.M.; Hossain, M.S.; Hassanain, E.; Alhamid, M.F.; Guizani, M. Blockchain and IoT-based cognitive edge framework for sharing economy services in a smart city. *IEEE Access* **2019**, *7*, 18611–18621. [CrossRef]
43. Peck, M.E. Blockchains: How they work and why they'll change the world. *IEEE Spectr.* **2017**, *54*, 26–35. [CrossRef]
44. Angraal, S.; Krumholz, H.M.; Schulz, W.L. Blockchain technology: Applications in health care. *Circ. Cardiovasc. Qual. Outcomes* **2017**, *10*, e003800. [CrossRef]
45. Moura, T.; Gomes, A. Blockchain voting and its effects on election transparency and voter confidence. In Proceedings of the 18th Annual International Conference on Digital Government Research, Staten Island, NY, USA, 7–9 June 2017.
46. Aggarwal, S.; Chaudhary, R.; Aujla, G.S.; Kumar, N.; Choo, K.K.R.; Zomaya, A.Y. Blockchain for smart communities: Applications, challenges and opportunities. *J. Netw. Comput. Appl.* **2019**, *144*, 13–48. [CrossRef]
47. Yeoh, P. Regulatory issues in blockchain technology. *J. Financ. Regul. Compliance* **2017**. [CrossRef]
48. Habibzadeh, H.; Nussbaum, B.H.; Anjomshoa, F.; Kantarci, B.; Soyata, T. A survey on cybersecurity, data privacy, and policy issues in cyber-physical system deployments in smart cities. *Sustain. Cities Soc.* **2019**, *50*, 101660. [CrossRef]
49. Jin, D.; Hannon, C.; Li, Z.; Cortes, P.; Ramaraju, S.; Burgess, P.; Buch, N.; Shahidehpour, M. Smart street lighting system: A platform for innovative smart city applications and a new frontier for cyber-security. *Electr. J.* **2016**, *29*, 28–35. [CrossRef]
50. Vitunskaite, M.; He, Y.; Brandstetter, T.; Janicke, H. Smart cities and cyber security: Are we there yet? A comparative study on the role of standards, third party risk management and security ownership. *Comput. Secur.* **2019**, *83*, 313–331. [CrossRef]
51. D'Onofrio, S.; Portmann, E. Cognitive computing in smart cities. *Inform. Spektrum* **2017**, *40*, 46–57. [CrossRef]
52. Chen, M.; Herrera, F.; Hwang, K. Cognitive computing: Architecture, technologies and intelligent applications. *IEEE Access* **2018**, *6*, 19774–19783. [CrossRef]
53. Honarvar, A.R.; Sami, A. Towards sustainable smart city by particulate matter prediction using urban big data, excluding expensive air pollution infrastructures. *Big Data Res.* **2019**, *17*, 56–65. [CrossRef]
54. Moglia, M.; Cork, S.J.; Boschetti, F.; Cook, S.; Bohensky, E.; Muster, T.; Page, D. Urban transformation stories for the 21st century: Insights from strategic conversations. *Glob. Environ. Chang.* **2018**, *50*, 222–237. [CrossRef]
55. Mydlarz, C.; Salamon, J.; Bello, J.P. The implementation of low-cost urban acoustic monitoring devices. *Appl. Acoust.* **2017**, *117*, 207–218. [CrossRef]
56. Valls, F.; Redondo, E.; Fonseca, D.; Torres-Kompen, R.; Villagrasa, S.; Martí, N. Urban data and urban design: A data mining approach to architecture education. *Telemat. Inform.* **2018**, *35*, 1039–1052. [CrossRef]
57. Galbrun, E.; Pelechrinis, K.; Terzi, E. Urban navigation beyond shortest route: The case of safe paths. *Inf. Syst.* **2016**, *57*, 160–171. [CrossRef]
58. Oliveira, J. *Big Social Data and Urban Computing*; Springer International Publishing: New York, NY, USA, 2019.
59. Cicirelli, F.; Guerrieri, A.; Mastroianni, C.; Spezzano, G.; Vinci, A. *The Internet of Things for Smart Urban Ecosystems*; Springer: Cham, Switzerland, 2019.
60. Salim, F.; Haque, U. Urban computing in the wild: A survey on large scale participation and citizen engagement with ubiquitous computing, cyber physical systems, and Internet of Things. *Int. J. Hum. Comput. Stud.* **2015**, *81*, 31–48. [CrossRef]
61. Krieg, J.-G.; Jakllari, G.; Toma, H.; Beylot, A.L. Unlocking the smartphone's sensors for smart city parking. *Pervasive Mob. Comput.* **2018**, *43*, 78–95. [CrossRef]
62. Low, R.; Tekler, Z.D.; Cheah, L. An End-to-End Point of Interest (POI) Conflation Framework. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 779. [CrossRef]
63. Zhang, N.; Chen, H.; Chen, X.; Chen, J. ELM meets urban computing: Ensemble urban data for smart city application. In *Proceedings of ELM-2015 Volume 1: Theory, Algorithms and Applications (I)*; Springer International Publishing: New York, NY, USA, 2016; pp. 51–63.
64. Tekler, Z.D.; Low, R.; Yuen, C.; Blessing, L. Plug-Mate: An IoT-based occupancy-driven plug load management system in smart buildings. *Build. Environ.* **2022**, *223*, 109472. [CrossRef]
65. Chen, B.; Zeng, Q.; Cheng, Z. Quasi-holography computational model for urban computing. *Vis. Inform.* **2019**, *3*, 81–86. [CrossRef]
66. Huang, L.; Fu, Q.; Li, G.; Luo, B.; Chen, D.; Yu, H. Improvement of maximum variance weight partitioning particle filter in urban computing and intelligence. *IEEE Access* **2019**, *7*, 106527–106535. [CrossRef]
67. Malik, A.W.; Mahmood, I.; Ahmed, N.; Anwar, Z. Big data in motion: A vehicle-assisted urban computing framework for smart cities. *IEEE Access* **2019**, *7*, 55951–55965.
68. Mora, H.; Peral, J.; Ferrandez, A.; Gil, D.; Szymanski, J. Distributed Architectures for Intensive Urban Computing: A Case Study on Smart Lighting for Sustainable Cities. *IEEE Access* **2019**, *7*, 58449–58465. [CrossRef]
69. Meneguette, R.I.; Boukerche, A. Vehicular Clouds Leveraging Mobile Urban Computing Through Resource Discovery. *IEEE Trans. Intell. Transp. Syst.* **2019**, *21*, 2640–2647. [CrossRef]
70. Lah, O.; Fulton, L.; Arioli, M. Decarbonisation scenarios for transport and the role of urban mobility. In *Sustainable Urban Mobility Pathways*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 65–80.

71. da Cruz, S.M.S.; Costa, R.J.M. Enabling Smart City Provenance-Based Applications to Improve Urban Mobility in Brazilian Cities. In *Sustainable Transportation and Smart Logistics*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 439–466.
72. Fernández-Ares, A.; Mora, A.M.; Arenas, M.G.; García-Sánchez, P.; Romero, G.; Rivas, V.; Castillo, P.A.; Merelo, J.J. Studying real traffic and mobility scenarios for a Smart City using a new monitoring and tracking system. *Future Gener. Comput. Syst.* **2017**, *76*, 163–179. [CrossRef]
73. Joshi, M.; Vaidya, A.; Deshmukh, M. Sustainable transport solutions for the concept of smart city. *Sustain. Energy Transp. Technol. Policy* **2018**, 21–42. [CrossRef]
74. Ma, X.; Liu, C.; Wen, H.; Wang, Y.; Wu, Y.J. Understanding commuting patterns using transit smart card data. *J. Transp. Geogr.* **2017**, *58*, 135–145. [CrossRef]
75. Canitez, F. Transferring sustainable urban mobility policies: An institutional perspective. *Transp. Policy* **2020**, *90*, 1–12. [CrossRef]
76. Rad, T.G.; Sadeghi-Niaraki, A.; Abbasi, A.; Choi, S.M. A methodological framework for assessment of ubiquitous cities using ANP and DEMATEL methods. *Sustain. Cities Soc.* **2018**, *37*, 608–618.
77. Balduini, M.; Brambilla, M.; Della Valle, E.; Marazzi, C.; Arabghalizi, T.; Rahdari, B.; Vescovi, M. Models and practices in urban data science at scale. *Big Data Res.* **2019**, *17*, 66–84. [CrossRef]
78. Souza, T.I.; Aquino, A.L.; Gomes, D.G. A method to detect data outliers from smart urban spaces via tensor analysis. *Future Gener. Comput. Syst.* **2019**, *92*, 290–301. [CrossRef]
79. Alaba, F.A.; Othman, M.; Hashem, I.A.T.; Alotaibi, F. Internet of Things security: A survey. *J. Netw. Comput. Appl.* **2017**, *88*, 10–28. [CrossRef]
80. Ying, Z.; Cao, S.; Liu, X.; Ma, Z.; Ma, J.; Deng, R.H. PrivacySignal: Privacy-Preserving Traffic Signal Control for Intelligent Transportation System. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 16290–16303. [CrossRef]
81. Zhang, J.; Wang, F.Y.; Wang, K.; Lin, W.H.; Xu, X.; Chen, C. Data-driven intelligent transportation systems: A survey. *IEEE Trans. Intell. Transp. Syst.* **2011**, *12*, 1624–1639. [CrossRef]
82. Alam, M.R.; Reaz, M.B.I.; Ali, M.A.M. A review of smart homes—Past, present, and future. *IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.)* **2012**, *42*, 1190–1203. [CrossRef]
83. Fredericks, E.M.; Bowers, K.M.; Price, K.A.; Hariri, R.H. CAL: A Smart Home Environment for Monitoring Cognitive Decline. In Proceedings of the 2018 IEEE 38th International Conference on Distributed Computing Systems (ICDCS), Vienna, Austria, 2–5 July 2018.
84. Khan, W.M.; Zualkernan, I.A. SensePods: A ZigBee-Based Tangible Smart Home Interface. *IEEE Trans. Consum. Electron.* **2018**, *64*, 145–152. [CrossRef]
85. Shi, X.; Luo, J.; Luo, J.; Li, X.; Han, K.; Li, D.; Cao, X.; Wang, Z.L. Flexible Wood-Based Triboelectric Self-Powered Smart Home System. *ACS Nano* **2022**, *16*, 3341–3350. [CrossRef]
86. Vegni, A.M.; Biagi, M.; Cusani, R. Smart vehicles, technologies and main applications in vehicular ad hoc networks. In *Vehicular Technologies-Deployment and Applications*; BoD—Books on Demand: Norderstedt, Germany, 2013; pp. 3–20.
87. Omheni, N.; Bouabidi, I.; Gharsallah, A.; Zarai, F.; Obaidat, M.S. Smart mobility management in 5G heterogeneous networks. *Iet Netw.* **2017**, *7*, 119–128. [CrossRef]
88. Dragičević, T.; Siano, P.; Prabaharan, S.S. Future generation 5G wireless networks for smart grid: A comprehensive review. *Energies* **2019**, *12*, 2140.
89. Mo, Y.; Kim, T.H.J.; Brancik, K.; Dickinson, D.; Lee, H.; Perrig, A.; Sinopoli, B. Cyber–physical security of a smart grid infrastructure. *Proc. IEEE* **2011**, *100*, 195–209.
90. Mallett, A.; Jegen, M.; Philion, X.D.; Reiber, R.; Rosenbloom, D. Smart grid framing through coverage in the Canadian media: Technologies coupled with experiences. *Renew. Sustain. Energy Rev.* **2018**, *82*, 1952–1960. [CrossRef]
91. Hui, L.; Gui-rong, W.; Jian-ping, W.; Peiyong, D. Monitoring platform of energy management system for smart community. In Proceedings of the 2017 29th Chinese Control and Decision Conference (CCDC), Chongqing, China, 28–30 May 2017.
92. Kulkarni, P.; Farnham, T. Smart city wireless connectivity considerations and cost analysis: Lessons learnt from smart water case studies. *IEEE Access* **2016**, *4*, 660–672. [CrossRef]
93. Samuel, O.; Javaid, N.; Almogren, A.; Javed, M.U.; Qasim, U.; Radwan, A. A Secure Energy Trading System for Electric Vehicles in Smart Communities using Blockchain. *Sustain. Cities Soc.* **2022**, *79*, 103678. [CrossRef]
94. Khan, M.A.; Abbas, S.; Hasan, Z.; Fatima, A. Intelligent transportation system (ITS) for smart-cities using Mamdani fuzzy inference system. *Int. J. Adv. Comput. Sci. Appl.* **2018**, *9*. [CrossRef]
95. Menouar, H.; Guvenc, I.; Akkaya, K.; Uluagac, A.S.; Kadri, A.; Tuncer, A. UAV-enabled intelligent transportation systems for the smart city: Applications and challenges. *IEEE Commun. Mag.* **2017**, *55*, 22–28. [CrossRef]
96. Lin, I.-C.; Lin, C.Y.; Hung, H.M.; Cui, Q.; Chen, K.C. Autonomous vehicle as an intelligent transportation service in a smart city. In Proceedings of the 2017 IEEE 86th Vehicular Technology Conference (VTC-Fall), Toronto, ON, Canada, 24–27 September 2017.
97. Turner, S.W.; Uludag, S. Toward Smart Cities via the Smart Grid and Intelligent Transportation Systems. In *Smart Grid*; CRC Press: Boca Raton, FL, USA, 2017; pp. 117–166.
98. Naghibi, B.; Masoum, M.A.; Deilami, S. Effects of v2h integration on optimal sizing of renewable resources in smart home based on monte carlo simulations. *IEEE Power Energy Technol. Syst. J.* **2018**, *5*, 73–84. [CrossRef]
99. Ahsan, U.; Bais, A. Distributed smart home architecture for data handling in smart grid. *Can. J. Electr. Comput. Eng.* **2018**, *41*, 17–27. [CrossRef]

100. Khan, Z.A. Using energy-efficient trust management to protect IoT networks for smart cities. *Sustain. Cities Soc.* **2018**, *40*, 1–15. [CrossRef]
101. Tekler, Z.D.; Ono, E.; Peng, Y.; Zhan, S.; Lasternas, B.; Chong, A. ROBOD, room-level occupancy and building operation dataset. In *Building Simulation*; Tsinghua University Press: Beijing, China, 2022; Volume 15, pp. 2127–2137.
102. Dallel, O.; Ayed, S.B.; Taher, J.B.H. Secure iot-based emergency management system for smart buildings. In Proceedings of the 2021 IEEE Wireless Communications and Networking Conference (WCNC), Nanjing, China, 29 March–1 April 2021.
103. Dong, J.; Winstead, C.; Nutaro, J.; Kuruganti, T. Occupancy-based HVAC control with short-term occupancy prediction algorithms for energy-efficient buildings. *Energies* **2018**, *11*, 2427. [CrossRef]
104. Abdelhamid, S.; Hassanein, H.S.; Takahara, G. Reputation-aware, trajectory-based recruitment of smart vehicles for public sensing. *IEEE Trans. Intell. Transp. Syst.* **2017**, *19*, 1387–1400. [CrossRef]
105. Aloqaily, M.; Al Ridhawi, I.; Kantraci, B.; Mouftah, H.T. Vehicle as a resource for continuous service availability in smart cities. In Proceedings of the 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), Montreal, QC, Canada, 8–13 October 2017.
106. Li, L.; Liu, J.; Cheng, L.; Qiu, S.; Wang, W.; Zhang, X.; Zhang, Z. CreditCoin: A privacy-preserving blockchain-based incentive announcement network for communications of smart vehicles. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 2204–2220. [CrossRef]
107. Garg, S.; Singh, A.; Batra, S.; Kumar, N.; Yang, L.T. UAV-empowered edge computing environment for cyber-threat detection in smart vehicles. *IEEE Netw.* **2018**, *32*, 42–51. [CrossRef]
108. Fantin Irudaya Raj, E.; Appadurai, M. Internet of things-based smart transportation system for smart cities. In *Intelligent Systems for Social Good: Theory and Practice*; Springer Nature: Singapore, 2022; pp. 39–50.
109. Naseer, S.; Liu, W.; Sarkar, N.I. Energy-efficient massive data dissemination through vehicle mobility in smart cities. *Sensors* **2019**, *19*, 4735. [CrossRef] [PubMed]
110. Ray, A.K.; Bagwari, A. Study of smart home communication protocol's and security & privacy aspects. In Proceedings of the 2017 7th International Conference on Communication Systems and Network Technologies (CSNT), Nagpur, India, 11–13 November 2017.
111. de Oliveira Neto, J.S.; Silva, A.L.M.; Nakano, F.; Pérez-Álcazar, J.J.; Kofuji, S.T. When Wearable Computing Meets Smart Cities: Assistive Technology Empowering Persons with Disabilities. In *Smart Cities and Smart Spaces: Concepts, Methodologies, Tools, and Applications*; IGI Global: Hershey, PA, USA, 2019; pp. 1356–1376.
112. Zenkert, J.; Dornhofer, M.; Weber, C.; Ngoukam, C.; Fathi, M. Big data analytics in smart mobility: Modeling and analysis of the Aarhus smart city dataset. In Proceedings of the 2018 IEEE Industrial Cyber-Physical Systems (ICPS), Saint Petersburg, Russia, 15–18 May 2018.
113. Soriano, F.R.; Samper-Zapater, J.J.; Martinez-Dura, J.J.; Cirilo-Gimeno, R.V.; Plume, J.M. Smart mobility trends: Open data and other tools. *IEEE Intell. Transp. Syst. Mag.* **2018**, *10*, 6–16. [CrossRef]
114. Ahmad, M.; Amin, M.B.; Hussain, S.; Kang, B.H.; Cheong, T.; Lee, S. Health Fog: A novel framework for health and wellness applications. *J. Supercomput.* **2016**, *72*, 3677–3695. [CrossRef]
115. Pagani, G.A.; Aiello, M. From the grid to the smart grid, topologically. *Phys. A Stat. Mech. Appl.* **2016**, *449*, 160–175. [CrossRef]
116. Elzein, N.M.; Majid, M.A.; Hashem, I.A.T.; Yaqoob, I.; Alaba, F.A.; Imran, M. Managing big RDF data in clouds: Challenges, opportunities, and solutions. *Sustain. Cities Soc.* **2018**, *39*, 375–386. [CrossRef]
117. Kansara, K.; Zaveri, V.; Shah, S.; Delwadkar, S.; Jani, K. Sensor based automated irrigation system with IOT: A technical review. *Int. J. Comput. Sci. Inf. Technol.* **2015**, *6*, 5331–5333.
118. Zafar, R.; Mahmood, A.; Razzaq, S.; Ali, W.; Naeem, U.; Shehzad, K. Prosumer based energy management and sharing in smart grid. *Renew. Sustain. Energy Rev.* **2018**, *82*, 1675–1684. [CrossRef]
119. Nam, T.; Pardo, T.A. Conceptualising smart city with dimensions of technology, people, and institutions. In Proceedings of the 12th Annual International Digital Government Research Conference: Digital Government Innovation in Challenging Times, ACM, College Park, MD, USA, 12–15 June 2011.
120. Milanés-Montero, M.I.; Barrero-González, F.; Pando-Acedo, J.; González-Romera, E.; Romero-Cadaval, E.; Moreno-Munoz, A. Smart Community Electric Energy Micro-Storage Systems with Active Functions. *IEEE Trans. Ind. Appl.* **2018**, *54*, 1975–1982. [CrossRef]
121. Anwar, R.W.; Ali, S. Smart Cities Security Threat Landscape: A Review. *Comput. Inform.* **2022**, *41*, 405–423. [CrossRef]
122. Cerrudo, C.; Hasbini, A.; Russell, B. *Cyber Security Guidelines for Smart City Technology Adoption*; Cloud Security Alliance: Bellingham, WA, USA, 2015.
123. Heo, G.; Chae, K.; Doh, I. Hierarchical Blockchain-Based Group and Group Key Management Scheme Exploiting Unmanned Aerial Vehicles for Urban Computing. *IEEE Access* **2022**, *10*, 27990–28003. [CrossRef]
124. Jansen, W.A.; Grance, T. *Guidelines on Security and Privacy in Public Cloud Computing*; Special Publication (NIST SP), National Institute of Standards and Technology: Gaithersburg, MD, USA, 2011.
125. Bak, M.A. Computing fairness: Ethics of modeling and simulation in public health. *Simulation* **2022**, *98*, 103–111. [CrossRef]
126. Fu, K.; Alhamadani, A.; Ji, T.; Lu, C.T. Batman or the joker? the powerful urban computing and its ethics issues. *Sigspatial Spec.* **2019**, *11*, 16–25. [CrossRef]
127. Bohge, M.; Trappe, W. An authentication framework for hierarchical ad hoc sensor networks. In Proceedings of the 2nd ACM Workshop on Wireless Security, San Diego, CA, USA, 19 September 2003.

128. Zhu, S.; Setia, S.; Jajodia, S. LEAP+: Efficient security mechanisms for large-scale distributed sensor networks. *ACM Trans. Sens. Netw. (TOSN)* **2006**, *2*, 500–528. [CrossRef]
129. Li, S.; Tryfonas, T.; Li, H. The Internet of Things: A security point of view. *Internet Res.* **2016**, *26*, 337–359. [CrossRef]
130. Jing, Q.; Vasilakos, A.V.; Wan, J.; Lu, J.; Qiu, D. Security of the Internet of Things: Perspectives and challenges. *Wirel. Netw.* **2014**, *20*, 2481–2501. [CrossRef]
131. Frizzo-Barker, J.; Chow-White, P.A.; Mozafari, M.; Ha, D. An empirical study of the rise of big data in business scholarship. *Int. J. Inf. Manag.* **2016**, *36*, 403–413. [CrossRef]
132. Yinbiao, S.; Lee, K.; Lanctot, P.; Jianbin, F.; Hao, H.; Chow, B.; Desbenoit, J.P. Internet of Things: Wireless Sensor Networks. White Paper, International Electrotechnical Commission. Available online: https://www.iec.ch.2014:11 (accessed on 18 December 2022).
133. Anjum, A.; Ahmed, T.; Khan, A.; Ahmad, N.; Ahmad, M.; Asif, M.; Reddy, A.G.; Saba, T.; Farooq, N. Privacy preserving data by conceptualising smart cities using MIDR-Angelization. *Sustain. Cities Soc.* **2018**, *40*, 326–334. [CrossRef]
134. Anjum, A.; Choo, K.K.R.; Khan, A.; Haroon, A.; Khan, S.; Khan, S.U.; Ahmad, N.; Raza, B. An efficient privacy mechanism for electronic health records. *Comput. Secur.* **2018**, *72*, 196–211. [CrossRef]
135. Islam, S.H.; Obaidat, M.S.; Vijayakumar, P.; Abdulhay, E.; Li, F.; Reddy, M.K.C. A robust and efficient password-based conditional privacy preserving authentication and group-key agreement protocol for VANETs. *Future Gener. Comput. Syst.* **2018**, *84*, 216–227. [CrossRef]
136. Kitchin, R. The ethics of smart cities and urban science. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **2016**, *374*, 20160115. [CrossRef] [PubMed]
137. Baldini, G.; Botterman, M.; Neisse, R.; Tallacchini, M. Ethical design in the internet of things. *Sci. Eng. Ethics* **2018**, *24*, 905–925. [CrossRef]
138. Mittelstadt, B. Ethics of the health-related internet of things: A narrative review. *Ethics Inf. Technol.* **2017**, *19*, 157–175. [CrossRef]
139. Gandia, R. City Outlines Travel Diary Plan to Determine Future Transportation Needs. Calgary Sun. 2012. Available online: https://calgarysun.com/2012/01/11/city-outlines-travel-diary-plan-to-determine-future%02transportation-needs (accessed on 20 May 2021).
140. Jiang, S.; Fiore, G.A.; Yang, Y.; Ferreira, J., Jr.; Frazzoli, E.; González, M.C. A review of urban computing for mobile phone traces: Current methods, challenges and opportunities. In Proceedings of the 2nd ACM SIGKDD International Workshop on Urban Computing, Chicago, IL, USA, 11 August 2013.
141. Yuan, J.; Zheng, Y.; Xie, X. Discovering regions of different functions in a city using human mobility and POIs. In Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Beijing China, 12–16 August 2012.
142. Sheng, C.; Zheng, Y.; Hsu, W.; Lee, M.L.; Xie, X. Answering top-k similar region queries. In *Database Systems for Advanced Applications: 15th International Conference, DASFAA 2010, Tsukuba, Japan, 1–4 April 2010*; Springer: Berlin/Heidelberg, Germany, 2010.
143. Zheng, Y.; Liu, F.; Hsieh, H.P. U-air: When urban air quality inference meets big data. In Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Chicago, IL, USA, 11–14 August 2013.
144. Becker, R.A.; Caceres, R.; Hanson, K.; Loh, J.M.; Urbanek, S.; Varshavsky, A.; Volinsky, C. A tale of one city: Using cellular network data for urban planning. *IEEE Pervasive Comput.* **2011**, *10*, 18–26. [CrossRef]
145. Demissie, M.G.; de Almeida Correia, G.H.; Bento, C. Exploring cellular network handover information for urban mobility analysis. *J. Transp. Geogr.* **2013**, *31*, 164–170. [CrossRef]
146. Calabrese, F.; Diao, M.; Di Lorenzo, G.; Ferreira, J., Jr.; Ratti, C. Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. *Transp. Res. Part C Emerg. Technol.* **2013**, *26*, 301–313. [CrossRef]
147. Liu, T.; Zheng, Y.; Liu, L.; Liu, Y.; Zhu, Y. Methods for sensing urban noises. Tec. Rep. MSR-TR-2014-66 2014. Available online: https://www.microsoft.com/en-us/research/publication/methods-for-sensing-urban-noises/ (accessed on 1 June 2021).
148. Ross, Z.; Kheirbek, I.; Clougherty, J.E.; Ito, K.; Matte, T.; Markowitz, S.; Eisl, H. Noise, air pollutants and traffic: Continuous measurement and correlation at a high-traffic location in New York City. *Environ. Res.* **2011**, *111*, 1054–1063. [CrossRef]
149. Wang, Y.; Zheng, Y.; Liu, T. A noise map of New York City. In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication, Seattle, WA, USA, 13–17 September 2014.
150. Martí, I.G.; Rodríguez, L.E.; Benedito, M.; Trilles, S.; Beltrán, A.; Díaz, L.; Huerta, J. Mobile application for noise pollution monitoring through gamification techniques. In *International Conference on Entertainment Computing*; Springer: Berlin/Heidelberg, Germany, 2012.
151. Santini, S.; Ostermaier, B.; Vitaletti, A. First experiences using wireless sensor networks for noise pollution monitoring. In Proceedings of the Workshop on Real-World Wireless Sensor Networks, New York, NY, USA, 1 April 2008.
152. Zheng, Z.; Xie, S.; Dai, H.N.; Chen, W.; Chen, X.; Weng, J.; Imran, M. An overview on smart contracts: Challenges, advances and platforms. *Future Gener. Comput. Syst.* **2020**, *105*, 475–491. [CrossRef]
153. Zhang, F.; Wilkie, D.; Zheng, Y.; Xie, X. Sensing the pulse of urban refueling behavior. In Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Zurich, Switzerland, 8–12 September 2013.
154. Shang, J.; Zheng, Y.; Tong, W.; Chang, E.; Yu, Y. Inferring gas consumption and pollution emission of vehicles throughout a city. In Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, New York, NY, USA, 24–27 August 2014.

155. Dusparic, I.; Harris, C.; Marinescu, A.; Cahill, V.; Clarke, S.l. Multi-agent residential demand response based on load forecasting. In Proceedings of the 2013 1st IEEE Conference on Technologies for Sustainability (SusTech), Portland, Oregon, 1–2 August 2013.
156. Momtazpour, M.; Butler, P.; Ramakrishnan, N.; Hossain, M.S.; Bozchalui, M.C.; Sharma, R. Charging and storage infrastructure design for electric vehicles. *ACM Trans. Intell. Syst. Technol. (TIST)* **2014**, *5*, 1–27. [CrossRef]
157. Malandra, F.; Chiquette, L.O.; Lafontaine-Bédard, L.P.; Sansò, B. Traffic characterisation and LTE performance analysis for M2M communications in smart cities. *Pervasive Mob. Comput.* **2018**, *48*, 59–68. [CrossRef]
158. Javidroozi, V.; Shah, H.; Feldman, G. Urban Computing and Smart Cities: Towards Changing City Processes by Applying Enterprise Systems Integration Practices. *IEEE Access* **2019**, *7*, 108023–108034. [CrossRef]
159. Nguyen, G.T.H.; Shimadera, H.; Uranishi, K.; Matsuo, T.; Kondo, A. Numerical assessment of PM2.5 and O_3 air quality in Continental Southeast Asia: Impacts of potential future climate change. *Atmos. Environ.* **2019**, *215*, 116901. [CrossRef]
160. Payus, C.M.; Syazni, M.N.; Sentian, J. Extended air pollution index (API) as tool of sustainable indicator in the air quality assessment: El-Nino events with climate change driven. *Heliyon* **2011**, *8*, e09157. [CrossRef]
161. Usmani, R.S.A.; Pillai, T.R.; Hashem, I.A.T.; Marjani, M.; Shaharudin, R.B.; Latif, M.T. Artificial intelligence techniques for predicting cardiorespiratory mortality caused by air pollution. *Int. J. Environ. Sci. Technol.* **2022**, 1–12. [CrossRef]
162. Li, Y.; Guo, J.E.; Sun, S.; Li, J.; Wang, S.; Zhang, C. Air quality forecasting with artificial intelligence techniques: A scientometric and content analysis. *Environ. Model. Softw.* **2022**, *149*, 105329. [CrossRef]
163. Huang, Y.L.; Batterman, S. Residence location as a measure of environmental exposure: A review of air pollution epidemiology studies. *J. Expo. Sci. Environ. Epidemiol.* **2000**, *10*, 66–85. [CrossRef]
164. Pinder, R.W.; Klopp, J.M.; Kleiman, G.; Hagler, G.S.; Awe, Y.; Terry, S. Opportunities and challenges for filling the air quality data gap in low-and middle-income countries. *Atmos. Environ.* **2019**, *215*, 116794. [CrossRef]
165. Commane, R.; Schiferl, L.D. Climate mitigation policies for cities must consider air quality impacts. *Chem* **2022**, *8*, 910–923. [CrossRef]
166. Suarez-Bertoa, R.; Astorga, C. Unregulated emissions from light-duty hybrid electric vehicles. *Atmos. Environ.* **2016**, *136*, 134–143. [CrossRef]
167. Lee, C.H.; Wu, C.H. Collecting and mining big data for electric vehicle systems using battery modeling data. In Proceedings of the 2015 12th International Conference on Information Technology-New Generations, Las Vegas, NV, USA, 13–15 April 2015; pp. 626–631.
168. Galus, M.D.; Andersson, G. Demand management of grid connected plug-in hybrid electric vehicles (PHEV). In Proceedings of the 2008 IEEE Energy 2030 Conference, Atlanta, Georgia, 17–18 November 2008; pp. 1–8.
169. Pokorný, J.; Škoda, P.; Zelinka, I.; Bednárek, D.; Zavoral, F.; Kruliš, M.; Šaloun, P. Big data movement: A challenge in data processing. In *Big Data in Complex Systems*; Springer: Cham, Switzerland, 2015; pp. 29–69.
170. Salman, M.; Long, X.; Dauda, L.; Mensah, C.N. The impact of institutional quality on economic growth and carbon emissions: Evidence from Indonesia, South Korea and Thailand. *J. Clean. Prod.* **2019**, *241*, 118331. [CrossRef]
171. Munjal, R.; Liu, W.; Li, X.J.; Gutierrez, J. A neural network-based sustainable data dissemination through public transportation for smart cities. *Sustainability* **2020**, *12*, 10327. [CrossRef]
172. Ahmad, M.O.; Ahad, M.A.; Alam, M.A.; Siddiqui, F.; Casalino, G. Cyber-Physical Systems and Smart Cities in India: Opportunities, Issues, and Challenges. *Sensors* **2021**, *21*, 7714. [CrossRef] [PubMed]
173. Broo, D.G. Transdisciplinarity and three mindsets for sustainability in the age of cyber-physical systems. *J. Ind. Inf. Integr.* **2022**, *27*, 100290. [CrossRef]
174. Pundir, A.; Singh, S.; Kumar, M.; Bafila, A.; Saxena, G.J. Cyber-Physical Systems Enabled Transport Networks in Smart Cities: Challenges and Enabling Technologies of the New Mobility Era. *IEEE Access* **2022**, *10*, 16350–16364. [CrossRef]
175. Nagarajan, S.M.; Deverajan, G.G.; Bashir, A.K.; Mahapatra, R.P.; Al-Numay, M.S. IADF-CPS: Intelligent Anomaly Detection Framework towards Cyber Physical Systems. *Comput. Commun.* **2022**, *188*, 81–89. [CrossRef]
176. Feng, Z.; Qu, H.; Yang, S.H.; Ding, Y.; Song, J. A survey of visual analytics in urban area. *Expert Syst.* **2022**, *9*, e13065. [CrossRef]
177. Greenland, S.; Mansournia, M.A.; Altman, D.G. Sparse data bias: A problem hiding in plain sight. *BMJ* **2016**, *352*, i1981. [CrossRef]
178. Kanwal, M.; Malik, A.W.; Rahman, A.U. Mahmood I, Shahzad M. Sustainable vehicle-assisted edge computing for big data migration in smart cities. *IEEE Internet Things J.* **2019**, *7*, 1857–1871. [CrossRef]
179. Zhang, D.; Rodrigues, J.J.; Zhai, Y.; Sezaki, K. 5G and Beyond Technology-Enabled Remote Health. *IEEE Wirel. Commun.* **2021**, *28*, 44–45. [CrossRef]
180. Vitello, P.; Capponi, A.; Fiandrino, C.; Cantelmo, G.; Kliazovich, D. Mobility-driven and energy-efficient deployment of edge data centers in urban environments. *IEEE Trans. Sustain. Comput.* **2021**, *7*, 736–748. [CrossRef]
181. Sajjad, M.M.; Bernardos, C.J.; Jayalath, D.; Tian, Y.C. Inter-Slice Mobility Management in 5G: Motivations, Standard Principles, Challenges, and Research Directions. *IEEE Commun. Stand. Mag.* **2011**, *6*, 93–100. [CrossRef]
182. Alsamhi, S.H.; Shvetsov, A.V.; Kumar, S.; Hassan, J.; Alhartomi, M.A.; Shvetsova, S.V.; Sahal, R.; Hawbani, A. Computing in the Sky: A Survey on Intelligent Ubiquitous Computing for UAV-Assisted 6G Networks and Industry 4.0/5.0. *Drones* **2022**, *6*, 177. [CrossRef]
183. Cook, D.J.; Das, S.K. Pervasive computing at scale: Transforming the state of the art. *Pervasive Mob. Comput.* **2012**, *8*, 22–35. [CrossRef]

184. Costa, D.G.; Peixoto, J.P.J.; Jesus, T.C.; Portugal, P.; Vasques, F.; Rangel, E.; Peixoto, M. A Survey of Emergencies Management Systems in Smart Cities. *IEEE Access* **2022**, *10*, 61843–61872. [CrossRef]
185. Regulation: Regulation (EU) 2016/679 of the European Parliament and of the Council. 2016, p. 2016. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R0679 (accessed on 18 December 2022).
186. Streitz, N. Citizen-centred design for humane and sociable hybrid cities. In Proceedings of the Hybrid City 2015—Data to the People, Athens, Greece, 17–19 September 2015; pp. 17–20.
187. Streitz, N. Smart cities need privacy by design for being humane. In *What Urban Media Art Can Do–Why When Where and How*; Avedition: Stuttgart, Germany, 2016; pp. 268–274.
188. Streitz, N.; Charitos, D.; Kaptein, M.; Böhlen, M. Grand challenges for ambient intelligence and implications for design contexts and smart societies. *J. Ambient. Intell. Smart Environ.* **2019**, *11*, 87–107. [CrossRef]
189. Streitz, N. Beyond 'smart-only'cities: Redefining the 'smart-everything' paradigm. *J. Ambient. Intell. Humaniz. Comput.* **2019**, *10*, 791–812. [CrossRef]
190. Pira, M. A novel taxonomy of smart sustainable city indicators. *Humanit. Soc. Sci. Commun.* **2021**, *8*, 197. [CrossRef]