smart cities

Article

The Dual Role of Artificial Intelligence in Developing Smart Cities

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Abstract: Defining smart city pillars, and their nature and essence, continues to be debated in the scientific literature. The vast amount of information collected by electronic devices, often regarded merely as a means of rationalizing the use of resources and improving efficiency, could also be considered as a pillar. Information by itself cannot be deciphered or understood without analysis performed by algorithms based on Artificial Intelligence. Such analysis extracts new forms of knowledge in the shape of correlations and patterns used to support the decision-making processes associated with governance and, ultimately, to define new policies. Alongside information, energy plays a crucial role in smart cities as many activities that lead to growth in the economy and employment depend on this pillar. As a result, it is crucial to highlight the link between energy and the algorithms able to plan and forecast the energy consumption of smart cities. The result of this paper consists in the highlighting of how AI and information together can be legitimately considered foundational pillars of smart cities only when their real impact, or value, has been assessed. Furthermore, Artificial Intelligence can be deployed to support smart grids, electric vehicles, and smart buildings by providing techniques and methods to enhance their innovative value and measured efficiency.

Keywords: smart city pillars; Artificial Intelligence; smart grids; electric vehicles; smart buildings

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1. Introduction

A process of transformation inevitably has a cost, which can be considerable when it involves a paradigmatical leap and affects the individuals. This change of perspective derives from a lack or incompleteness of policies able to manage one or more social problems, causing, as a result, a degradation with respect to the quality of life or even safety. The demographic explosion that started in 1950 has made our planet more and more densely populated, causing the uncontrolled growth of a larger and larger number of urban areas. In 2021, Tokyo-Yokohama had a population of 37,843,000; Jakarta had 30,539,000, and Delhi had 24,998,000 [1], raising dramatic problems related to transport, pollution, energy, poverty, and so forth. In this sense, scaling up the urban architecture is an approach that is hardly sustainable, from both the economic and the social points of view. As a result, one interpretation of the concept of a smart city could emerge from the need to adopt different perspectives on the usage of technology and to develop a deeper awareness of the role of the citizen. Even though the term smart city [2] was introduced in 2009 to denote an idealized city organized by means of intelligent automatisms, there is yet to be a common agreement on a comprehensive, universal definition (see Section 2.1).

Whereas there are conceptual variants in the determination of the term, according to Lee et al. [3], three factors can be used to identify a smart city: the technology, the people, and the institutions. As such, the goal of a smart city should be the integration of these three components to resolve urban problems and to help create more sustainable, livable environments for citizens. Adopting this perspective, a smart city can be defined as the connection effort among physical, social, technological, and business infrastructures to improve operational efficiency and the collective quality of life [4]. This connection should result in a framework composed of four general components, which can be summarized as smart communities, smart energies, smart transportation, and smart healthcare [5]. Data are the backbone of a smart city. In fact, data are used to drive the operation of a smart city, through monitoring, forecasting, and real-time management [6]. Smart city implementation is strictly connected to collection and data analysis. Accordingly, Silva et al. [5] have identified an architecture comprising four layers: the sensing, transmission, data management, and application layers. The sensing layer is necessary to collect the data, and it consists of a sensor network, which gathers data from various physical devices. The transmission layer is used to converge all the data sources and communication networks. The data management layer performs data storing and analysis to support decision-making tasks. The application layer is the mediator between the citizens and the data management layer, representing all the services available in a smart city. Through this theoretical architecture, IoT has been strongly associated with the concept of the smart city [7]. Recently, AI has started to be considered a powerful tool for the evolution of smart cities. AI-backed applications are still in a developmental phase, and their full potential has yet to be achieved [8]. However, the introduction of AI has already drawn attention to the potential double-edged sword effect, according to which negative consequences could go unnoticed as a result of a techno-optimistic bias. As advocated by Yigitcanlar et al. [9], there is a need to research the potential shortcomings of AI when applied to smart cities. Hence, the energy-related components of a smart city would be under consideration for this purpose, particularly in relation to the ethical dilemmas related to environmental concerns and the complementary potential policies. In fact, the goal of decarbonization is emerging as the main goal in the evolution of smart cities. Cities, in particular, have long been associated with high generations of greenhouse emissions. In this context, stationary energy is one of the largest contributors to the greenhouse emissions of cities, along with the transportation sector [10]. Most importantly, a relatively small number of urban areas appear to account for a disproportionate share of the world's carbon footprint; hence, this degree of concentration indicates that, in many cases, local-level governments have a jurisdiction over emissions of the same order of magnitude as national governments [11]. This call for action is of great importance as according to the International Energy Agency, global energy-related carbon dioxide emissions rose by 6 percent in 2021, reaching a level of 36.3 billion tonnes, the highest ever recorded [12].

Although the term pillar is not always well defined within the definition of the smart city (see Schipper et al. [13] for an overview), its definition generally revolves around governance, economy, mobility, energy, and people and does not consider the pervasive influence of information (in the shape of Big Data) and, more specifically, AI. However, the effective value and governance of both with regard to smart cities is a relatively new topic, and it deserves a thorough analysis.

An interesting challenge consists in the assessment of smart city pillars in terms of (i) a value that can change over a period of time and that is defined by the contraposition between the cost related to its realization and the resulting benefits to the citizens and the environment and (ii) the definition of the policies and monitoring techniques. As a result, the contribution of this work consists of (i) an analysis of the value and the principles governing information with relation to the Internet of Things (IoT) and, more generally, Big Data when deployed towards smart cities; (ii) a discussion of the value of AI within smart cities, especially with regard to what concerns the impact on the environment; and (iii) a review of whether energy-related components of a smart city may benefit or not from the introduction of AI applications.

This paper is organized as follows: Section 2 reviews the methodology for the identification of the data; Section 3 discusses the value of information and its governance when it is originated from IoT devices on one side and as a whole on the other, such as when it is exploited in terms of directing citizens in the shape of nudging; Section 4 debates the value of AI per se in terms of the impact on the environment; Section 5 reviews the environmental challenges of the energy-related components of a smart city when supported by AI; Section 6 discusses the contribution of AI to smart cities by presenting a few case studies. Finally, the article draws some conclusions in Section 7.

2. Methodology for the Collection and Review of the Data

The research area surrounding the concept of smart cities is very dynamic and in continuous evolution. This has resulted in a vast knowledge being produced that allows for an integrative literature review methodology. Hence, a careful collection and filtering of relevant academic papers has been performed for the scope. Two databases have been used: Google Scholar and the Catholic University of the Sacred Heart's Online Public Access Catalogue (OPAC). The primary focus was to collect peer-reviewed papers published by high-quality publishers. The aim was to retrieve studies that were pertinent to previously formulated questions:

- What studies concern the development of AI in the three proposed energy-related areas (smart grid, EVs, and smart building) of a smart city?
- What research has been carried out in relation to the negative effects that AI can have when applied in those areas?
- How effective have nudging practices empirically been in inducing energy-saving behavior or in switching to renewable energy?
- Is AI a sustainable technology? What about data collection techniques?

The references of the collected papers were used to find additional resources to expand the analysis. The inclusion criteria were based on the relevancy of an academic paper in comparison with the issues planned for investigation, with the objective of providing a good balance between empirical research and qualitative studies. Instead, exclusion was considered for research with repetitive results or for research that could not be contextualized in the development of a smart city.

After an exhaustive evaluation of all the retrieved academic papers, additional secondary data (e.g., reports, websites of governmental agencies, newspaper articles from reputable publishers …) were searched for on Google to further support the emerging findings and to build up the case studies presented in Section 6. A deductive approach has been used to derive the final considerations.

Finally, with regard to the other existing literature, this work aims to present an objective analysis of AI, avoiding approaches that are either over-positive [14] or biased by anthropocentric interpretations of AI, where the latter would be regarded as a convoluted issue and potentially dangerous [15,16].

2.1. The Concept of "Smart City" and the Contribution of This Research

In the scientific literature, the assortment around the definition of a smart city (Table 1) has contributed to ideals and expectations that lack a corresponding concreteness in the real world [17]. Albino et al. [18] have supported the idea that the uniqueness of the objectives that may be endorsed may compromise a universal assessment of a smart city. With regard to this matter, Burns et al. [19] have discussed how the variety of smart city initiatives around the world has produced a term that is strictly related to the contexts in which it is deployed.

Table 1. Some definitions of the term "smart city" in the scientific literature.

Source	Definition
Harrison et al. [4]	"Connecting the physical infrastructure, the IT infrastructure, the social infrastructure, and the business infrastructure to leverage the collective intelligence of the city".
Almirall et al. [20]	"A concept that encompasses most of the areas where local governments operate: transportation, civic entrepreneurship, democratic transparency, clean energy, and services provision".

Table 1. *Cont.*

Source	Definition
Mohanty et al. [7]	"A place where traditional networks and services are made more flexible, efficient, and sustainable with the use of information, digital and telecommunication technologies, to improve its operations for the benefit of its inhabitants".
Park et al. [21]	"A concept has gained substantial attention over the last few years, as it applies advances in the Internet of Things (IoT) technology to enhance the quality and efficiency of services and resources"
Wang et al. [6]	"The idea ... is to use information technology to drive the operation of the city, which includes monitoring, forecasting, and real-time management. The combination of IoT and AI can replace the traditional means of managers in the past."
Lazaroiu and Roscia [22]	"The large and small districts are proposing a new city model, called the smart city, which represents a community of average technology size, interconnected and sustainable, comfortable, attractive and secure."

The study of Ahvenniemi et al. [23] is among the first to highlight the importance of the sustainable development of smart cities and how the employment of new technologies should not be an end in itself. In particular, from this perspective, Kramers et al. [24] have assessed how different ICT solutions could be used to reduce energy consumption in smart cities. More recently, Hoang et al. [25] have reviewed the introduction of renewable resources into smart cities, along with the potential challenges. As electric vehicles are becoming an important topic in the discussion on the demand-side of a smart grid, the barriers to their adoption have been comprehensively evaluated by Adhikari et al. [26] in connection with the energy requirement. Similarly, the argument has been assessed by Sanguesa et al. [27], but in the specific framework of smart cities. While many AI applications have been developed for the smart grid, and Omitaomu and Niu [28] have provided a complete survey on the matter, there is yet to be an analysis of whether the introduction of AI can be an actual solution to environmental concerns. In fact, Yigitcanlar et al. [9] have provided the general shortfalls of AI when deployed in smart cities. It is important to point out that data collection can not only support AI but also nudging techniques. The idea of hypernudging has been presented by Yeung [29], and it has been further enriched by the work of Ranchordás [30] with regard to the academic literature on smart cities in terms of legal and ethical issues. Hence, a review of the effectiveness of hypernudge techniques aimed at conscious energy consumption will be provided to expand this discussion.

3. Evaluation of Information

According to The Economist [31], not only are data the new oil, but it is even reasonable to talk about a data economy as a force driving the economic market. Aside from text, information over the internet is delivered in different shapes, ranging from the visual (i.e., YouTube videos), to emoticons, to likes and tweets, although there is an impressive amount of data revolving around individuals that is generally overlooked. For instance, every time we visit a website, the deployment of cookies on our device makes the website able to recognize us in the future; the simple act of using a cash withdrawal machine triggers a camera that records the movements of the customer; every financial transaction is meticulously recorded and preserved; supermarkets and commercial chains study our shopping habits and propose discounted items according to customers' previous purchases; navigator systems embedded in smartphones will send the users an e-mail with a monthly report about the visited places. IoT has emerged as the technical backbone of the information and communication technology (ICT) current architecture (see [7,32] regarding cloud computing technology). Sensors are the most important components of an IoT system. The design of a smart city application is contingent upon the way the sensors are deployed; mobile, stationary, and crowd-sourced sensors perform different methods of data collection [33]. Whereas stationary sensors always monitor the same area, the mobile ones are implemented on vehicles, such as buses or garbage trucks. Crowd-sourced sensors are a special class of mobile sensors, where the digital devices of the citizens are used to monitor the surrounding environment. Cloud computing technologies provide data storage and platforms to process the sensors' data and to deploy smart city applications. According to Bauer, there are mainly four different data analytics approaches that can be identified in smart cities: descriptive, diagnostic, predictive, and prescriptive analytics.

Big Data is a recent paradigm denoting a large amount of unstructured data deriving, for example, from sensors typically deployed in an IoT structure in the e-health domain. The so-called "4 Vs" identify some of the crucial issues emerging with Big Data, i.e., (i) volume, (ii) velocity, (iii) variety, and (iv) veracity: specifically, the latter poses some problems revolving around the validity of data and, indirectly, implies the existence of procedures protecting access to information. As highlighted by Hashem et al. [34], Big Data represents a remarkable value in smart city development in different aspects: (i) weather data, in order to prepare the citizens for adverse meteorological conditions, see Chin et al. [35]; (ii) better quality of life, resulting from the facilitated access to government procedures or, as pointed out by Chow et al. [36], even to public libraries; (iii) smart healthcare, following a more efficient monitoring of patients; Praman et al. [37] highlight that the Big Data concept has triggered a deeper change, going beyond the development of new IT architectures, as it embraces the social awareness of health issues; (iv) smart transportation, determined by a more rational choice of routes according to factors such as traffic peaks, pollution level, and safety criteria. See, for example, Gohar et al. [38] where the authors define an Intelligent Transportation System (ITS) able to transform an ordinary city into a smart city. The framework is composed of four modules, namely a Big Data Acquisition and Preprocessing Unit, a Big Data Processing Unit, a Big Data Analytics Unit, and a Data Visualization Unit. ITS is able to generate warnings when, for example, the level of traffic exceeds a given threshold. The final aspect is (v) smart governance. An example of a framework is given by Ju et al. [39]; the framework is structured into three layers: a data-merging layer, presenting citizen-centered panoramic data generated by assembling citizen-related big data, followed by a knowledge–discovery layer which, by using statistical methods, generates a profile of citizens in terms of urban public service delivery. The last component is a decision-making layer, supporting governance decision making by using data mining methods.

On the other hand, information ubiquity can bring different benefits, from a better and higher level of education (see Livingstone [40] for a fair assessment on the benefits and the difficulties) to the granting of access to distributed services to mentally disabled persons (Chadwick [41]). More specialized technologies, such as blockchain (a robust and resilient digital ledger of transactions being duplicated and distributed across the whole network of computer systems, see [42]), serve different applications revolving around smart cities. With regard to the former, Karale et al. [43] consider different applications based on blockchain in smart cities: (i) secure data communication, (ii) smart contracts (a transaction between two parties without an intermediary), (iii) citizen participation, (iv) economy, (v) renewable energy, (vi) safety, and (vii) health.

As data content regarding the individual is sensitive, proper regulation and legislative procedures have been put in place, from the General Data Protection Regulation approved by the EU Charter of Fundamental Rights [44] to the European Data Protection Board's guidelines on processing of personal data through video devices [45].

However, data can be found in not so obvious places, such as smartwatches communicating information regarding the physiological status of the human body, i.e., heartbeat, blood pressure, number of steps taken by a user in a day and so forth, to the software installed on our smartphones, which can be used to monitor bad habits—such as a sedentary lifestyle—and provide the user unsolicited recommendations about her health. Another—

perhaps hidden—source of data can be found in the garbage bin: for example, a bill of a supermarket reveals the preferences of a customer in terms of bought products, the size of a family and the favorite day for shopping (working days or weekends); bills about electricity or any other utilities provide information about the daily habits of a consumer. Furthermore, sensitive documents (such as an expired credit card), even if shredded, can be recomposed in their original form. Although this information may not be meaningful when taken separately, by an in-depth analysis it can lead to identity theft [46]. The neutrality of data is obviously a myth, as has emerged recently in some courts of justice in the U.S.A. [47], where the deployment of AI algorithms revealed that the serious failures in predicting violent crime were being affected by a bias based on race and prejudice in the data collection process. More generally, biased data can be used to influence opinions and beliefs.

With regard to monitoring and governing information, the different data sources pose different challenges. IoT devices are usually considered to be the basic components of Big Data architectures. Although this paradigm offers a wide scalability, traffic congestion in the network may occur, due to undersized nodes (in terms of hardware) or faults: these issues can be prevented by techniques where the performance of the architecture is studied by building a mathematical model and then simulating it in terms of discrete events (for example, see Sankaram [48]). Furthermore, a new paradigm has recently emerged called fog computing [49,50], where sophisticated data pre-processing can take place at the IoT level (therefore, locally), instead of the data being transmitted directly to cloud services, which is demanding to the latter's the entire processing and slows the system performance down.

Table 2 summarizes the different sources of information, their value, and the corresponding management techniques of each.

Table 2. Data value and its management.

Data Source	Value	Management/Monitoring
IoT	Data generation. Examples: eHealth, Transport, Weather	Integration within Big Data by means of frameworks. Fog computing
Blockchain	Security, Participation, Digital democracy	Distributed processing
Cloud	Data distribution, Liquid data	GDPR
Hidden data	Profiling.	Very hard to achieve
Cognitive bias	Biased algorithms (negative value)	Achievable by using algorithms correcting bias in data

Nudging for Energy Savings and Environmentally Aware Choices

The objective of nudging is to steer people in certain directions for their welfare and well-being, without affecting their freedom of choice [51]. Their behavior is influenced by how the choices are presented to their decision makers, or in other words, by the choice architecture. It is important to specify that nudging does not involve any direct form of economic incentives to influence the decision making, and it does not forbid any other options. One example of such a practice can be identified in the competition "Project Carbon Zero" held in Singapore for primary and secondary school, in which students were encouraged to learn energy-saving tips and to reach the goal of reducing their overall electricity usage at home by at least 10 percent [52]. The common commitment to reducing energy consumption and the information received on the issue of climate change were indeed effective in inducing people to make more environmental friendly choices. It follows that nudging could be of great importance in facilitating energy-saving and reducing greenhouse emissions, especially given the emerging complexity of how such issues can be effectively solved. It is believed that nudging could have great potential if expanded to promote pro-environmental behavior, and the technique has yet to receive adequate consideration for this purpose [53]. AI can be considered a promising tool in this context, which could lead to more environmentally aware choices concerning energy saving. To discuss this point, it is necessary to review the available forms of nudge, such that a theoretical assessment of whether AI can support such practices can be made. In the context of a smart city, it is also of great importance to understand how these types of nudges could be implemented and to understand the ethical issues related to them.

The enormous collection of data that is likely to happen in a smart city framework could facilitate the design of highly specific nudges, especially when fed into AI algorithms. This data-driven nudging technique has been referred to as hypernudge, which allows for a dynamic refinement of an individual's choice architecture [29]. The most significant difference from regular nudging techniques is that the latter only allow for universal, population-wide initiatives; thus, they may be less effective on a smaller scale. Thunström et al. [54] have pointed out that the distributional effects of a nudge may be far from optimal as they may fail to influence the individuals for which the policy itself was designed. From this perspective, hypernudge techniques may support more targeted pushes towards desired behaviors. There are different forms of nudges, from which Sunstein [51] has listed ten techniques: default rules, simplification, use of social norms, increase ease and convenience, disclosure, warnings, precommitment, reminders, elicit implementation intention, and information on past choices. However, in the context of reducing energy consumption, not all the nudging techniques have been proven effective on all occasions. In the case of shifting to an energy supplier that relies on renewable resources, a default transfer increases the number of individuals that adapt to the decision [55]. However, the technique of default rules in the form of enrollment in automatic bill payments has been shown to increase energy consumption [56]. In addition, other types of nudges do not represent the necessary encouragement. Social norms, which can be defined as a technique that relies on influencing people through peer comparison, seem to fail, particularly when not supported by monetary incentives [57,58]. Hence, disclosure of the cost savings appears with the reduction in energy consumption. Still, receiving constant information on energy consumption appears to better support the purpose of energy saving [59]. Moreover, warnings through visual representation tend to be a motivational aid [60], as well as tools supporting goal setting and commitments that can serve as an effective implementation intention to reduce energy consumption [52,61]. A study conducted by Ruokamo et al. [62] has shown that peer comparisons decrease electricity consumption only when combined with energy-saving tips, but most importantly, energy-saving behavior is more challenging to encourage within households that are less interested in reducing energy consumption whatever the motivation. Kendel et al. [63] suggest that high-income and low-income households should be engaged in energy-saving behavior by using different types of information and objectives. Apps that provide push notifications, which can be categorized as remainders, can be successful thanks to the advantage of the possible personalization [64]. The latter is an example of a hypernudge. With regard to this topic, AI could have the potential to support personalized forms of the types of nudges listed; yet, there appears to be a scarcity of AI-backed nudges. As previously discussed, AI-backed virtual assistants could have the potential to be a useful means of nudging inside consumers' houses to lower energy consumption. However, such technologies entail consumers paying a price to own them, such as with smart meters. As it comes as a choice, consumers may not be interested in acquiring energy-saving devices. Free riding can happen; some households might not respond to any incentive to purchase energy-saving appliances because they prefer to believe that greenhouse emissions can be attenuated by others [65]. However, is it ethical to use a private possession, such as a virtual assistant or a smartphone, to influence the behaviors of the owners? Two issues may arise with this form of hypernudge. The first is that the use of personal possessions may make the nudge less transparent and noticeable to the consumers, thus going against the guidelines of nudging. Similarly, the second is that opting out may be harder as it would be necessary to turn down some functionalities that may comprise the overall working of the device. Conversely, consumers may be willing to be subjected to recommendations and reminders but may then decide to ignore them with time. For instance, the effect of moral suasion for energy saving diminishes as the number of interventions increases [66]. Overall, the concept of hypernudging has been associated with the concept of a smart city in order to discuss the ethical concerns related to privacy, autonomy, and subtle manipulation. Even if it appears that most applications focus on targeting a single household to reduce energy consumption, all the critiques of the hypernudge can still be valid.

To conclude, in general, environmentally oriented nudges seem to be rather limited with respect to their behavioral effectiveness, and their impact may be highly context-dependent [67]. Moreover, they appear to work more effectively if they are complementary to incentive-based measures.

4. Evaluation of AI

The term AI denotes a discipline that stemmed from computer science and, specifically, from the work of A. Turing [68,69]. AI has been under severe criticism over the last century (partially losing its credibility in periods of time called "AI winters" [70], due to some unjustified claims), although it has recently been leading the development of industry 4.0 and IT companies [71].

Historically, AI has been evaluated according to its capacity for playing classic board games against humans [72] and then by taking into account more challenging competitions [73], although a full evaluation of the discipline requires a multidisciplinary perspective, including linguistics, psychology, cognitive sciences, philosophy, and ethics.

However, there are some aspects related to AI and its deployment that need to be analyzed. Computation has a cost determined by the time taken by a calculus system to execute one or more algorithms, which can be determined in terms of memory allocation, Central Processing Unit (CPU) usage, the time taken to perform bug fixing, and, finally, the energy consumption requested by a machine. The last factor refers literally to the power requested to feed hardware consisting of one or more servers and data centers. According to *Forbes* [74], 2.5 quintillion bytes of data were produced on a daily base in 2019 from different sources: users, Graphics Processor Units, healthcare devices, IOT sensors, and so forth. This growth has made more evident the inadequacy of the classical techniques representing data structures, such as the relational model (where data are represented in tables linked to each other through relationships), and of consolidated hardware infrastructures, based on centralized solutions providing on-demand services to clients. However, the innovation of data models, and logical and physical models, reflects the deep changes occurring in society and reflects different aspects: more and more entangled communications via social networks, remote, on-line labor, and entertainment based on digital multimedia (tablets, smart TVs, smartphones), just to name a few. The concept of the liquid society was introduced by the philosopher Zygmunt Bauman [75] to denote the change of social habits due to the establishment of a new paradigm based on the fragmentation of working activity as the internet has made it possible to connect people physically distant at an insignificant cost and, more generally, by the way in which ordinary people use and propagate heterogeneous information. The distributed data models recently built, where no center exists, suit well the need to deploy sensors collecting data continuously, which are pre-processed, indexed, catalogued, fragmented, and then reassembled to answer to complex queries, triggered either by search engines on the web or requested by specific applications belonging to the AI's realm.

Such an infrastructure comes with a non-negligeable cost. The emergence of new approaches—see, for example, edge computing [76], which is based on the concept of proximity in order to pre-process data as close as possible to the sensors—allows the reduction in the response time, the requested bandwidth, the computational effort, and, indirectly, the value of energy consumption. As a result, the adjective green, expressing the concern for an ethical, parsimonious, and rational exploitation of the available resources, can be applied within reason to smart cities and AI in different ways. By the term Red AI, Schwartz et al. [77] meant the impact caused by AI software by means of the carbon footprint. The problem, which is due to grow in time, is even more evident for those AI applications which are computationally intensive, such as Deep Learning and, in general, paradigms based on artificial neural networks, where a training activity on datasets is requested. The authors propose a simplified and yet convincing formula to consider some key indicators, such as the cost of processing one data example and neglecting some others, such as the number of epochs requested to train an algorithm. Contraposed to Red AI, Green AI aims at favoring a type of computation oriented to reduce energy consumption. To properly evaluate the nature of Green AI, the first step results in measuring quantitively the energy consumption taken by the execution of an AI algorithm. Typical connectionist approaches consist of Artificial Neuron Networks (ANN), which stem from Rosenblatt's perceptron [78] and are being further developed into a model of the human brain's neurons and dendrites. Formally, an ANN consists of a large number of cells able to perform a simple operation deployed into tiers. The neurons in the first tier receive the raw data, while the other tiers retrieve their input from the previous one; finally, the last one produces an output (i.e., a classification). The tiers are connected through weighted arcs. A neuron is activated or not depending on the value of an activation function calculated as the summation of the products between each input and the weight assigned to an incoming arc, plus a bias value. The learning process consists of an algorithm called backpropagation [79], where the weights of arcs are optimized according to a mathematical method called gradient descent, an iterative process that can be—according to the complexity of the ANN—computationally expensive.

Labbe [80] reviewed the work of OpenAI when training 45 terabytes of data and running a cluster of 512 V100 GPUs for nine days, resulting in 27,648 kWh measured against 27,648 kWh, which is the average household usage in the US. Saenko [81] debated the risks of applying inefficient training-language-processing AI (such as the one used by Google) to the continuously increasing data, proposing a novel paradigm meant to reduce the model size, known as a shapeshifter network. Specifically, Saenko targets a typical problem of ANNs called over-parametrization (i.e., when the number of parameters of the ANN is much larger than the number of training data). Some approaches—such as parameter pruning—mitigate the issue, although parameter-sharing techniques produce better results by reducing the number of weights in an ANN, resulting in a smaller amount of allocated memory. The approach proposed by Plummer et al. (Neural Parameter Allocation Search [82]) allows the generation of a high-performing model provided with a fixed number of parameters and a specific architecture, reducing considerably the computational complexity.

However, the issue regarding the energy consumption level affects IoT, which is based on the massive deployment of embedded sensors collecting data. A unique Internet Protocol (IP) address is associated with each component to send data over a network or to communicate with other devices. A component called the IoT Hub has the responsibility of assembling and transferring the data to more complex software systems, performing a deep analysis to, for example, discover new knowledge, data trends, and patterns and, ultimately, to forecast a significant aspect of a business, such as the level of pollution or the energy needed for a building. As a result, an IoT results in a combination of hardware and software. Tahiliani et al. [83] review the layer of IoT architecture organized into the different layers (perception, transport, processing, network and application) identified in sensing, communicating, processing, and communicating across the layers as the power-hungry components. The authors recall different techniques to optimize energy consumption (such as multi-hop) in transmission over long paths. The way in which the sensors work can be oriented to a scheduling that switches them off when they are not needed, as well as to data centers where the load is balanced according to dedicated algorithms. More generally, the areas subject to improvement concern (i) data processing, as the information flow can result in a bottleneck if the architecture has not been properly designed, (ii) perceiving, by limiting the activity of sensors, and finally (iii) processing, by reducing the computation complexity of the business analytics processes.

AI and Smart Cities

Smart cities share a strong bond with AI. Specifically, AI is emerging as a particular facilitator in the process of providing faster data analysis to identify current and probable future urban issues. Up to now, it has mainly been applied to providing accurate estimates for energy modeling and planning, supporting the adoption of renewable energy sources, developing tools for health care, and ensuring sustainability in mobility and transportation systems. Cugurullo [84] provides a definition of Urban Artificial Intelligences, including innovative concepts such as autonomous cars, drones and nanorobots, and a city brain as an instance of platform urbanism.

Smart city AI applications are still in an evolutionary phase, and their full potential has yet to be realized. Still, the introduction of AI has already drawn attention to the potential double-edged sword effect that can go unnoticed because of the techno-optimistic perception of a smart city; hence, social, ecological, and economic hidden costs may be ignored when there is support for current, unsustainable urban models [85]. There is the risk that structural inefficiency and counterproductive urban behaviors that date back to a time when there was less attention paid to scarce resources can be amplified by AI applications. Similarly, the social disparity may be accidentally reinforced, as highly connected citizens are more represented in datasets than children, marginalized groups, and older generations. Moreover, these omitted groups of citizens may compromise the interconnectivity that is at the base of smart city development.

For example, Ullah et al. [86] discuss the use of AI in different crucial aspects of a smart city, such as intelligent transportation systems, cyber-security, energy-efficient utilization of smart grids, and efficient deployment of automatic aerial vehicles, by using techniques of Deep Reinforcement Learning (whose idea consists in pairing the connectionist approach known as Artificial Neural Network (ANN) with another technique called Reinforcement Learning, where a machine learns how to classify new observations according to a deterministic system of awards and penalties). Machine Learning (ML), a branch of AI deploying statistical methods (supervised or not by a user) is deployed to forecast the behavior of crucial key factors of a smart city. With regard to traffic congestion, Akthar [87] reviews different ML methods, ranging from clustering models to ANNs; energy conservation in buildings is studied by Dounis [88], who joins two well-known AI techniques, Computational Intelligence and Mobile Agents, together with ambient intelligence; finally, see Masood et al. [89] for models predicting the amount of pollution using fuzzy logic (an alternative branch of logic to Boolean formalisms, where the yes/no contraposition is translated into a real number between zero and one).

Golubchikov et al. [90] claim that AI and robotics can be part of the deployment of smart cities. What emerges from the analysis of several case studies is a significant difference between Global North and Global South, with different social considerations. Specifically, the authors have grouped the cases into five clusters (automation, decision making, education, smart infrastructure, and smart mobility), with which cities can consider AI and robotics.

However, despite some paradigms related to statistical learning's (and more generally to Machine Learning's) claim to be able to cope with uncertainty, Batty [91] remains rather skeptical, especially when AI pretends to replace human activity with regard to city planning. Kassens-Noor [92] compares some aspects of AI when applied to smart cities, warning about the risks of full automation, questioning the actual purpose of connected autonomous vehicles, and finally, criticizing the impact of AI on a society once all the most repetitive jobs have been taken by machines. Similarly, Yigitcanlar [93] remarks on similar concerns as integrating AI within a smart city could determine more issues, such as a degradation of urban problems (unless paired with a system of democratic governance) and questions revolving around the concept of sustainable urbanism when AI is not used on holistic terms. Finally, Cugurullo [15] introduces the term "Frankenstein urbanism" to denote some of the risks in involving AI software inside smart cities' architecture, noting however that the same neologism deviates significantly from what AI claims to be as the term Frankenstein is clearly anthropocentric and somewhat biased by classical literature.

5. The Role of AI in Energy Issues

In this section, the objective is going to be the analysis of the energy-related elements of a smart city (Figure 1) and, in particular, their intersection with AI to tackle environmental concerns. The three sectors that are going to be under consideration are electricity generation, transportation, and buildings, given that they are the major determinants of greenhouse emissions [94]. It is expected that AI might be able to drive decarbonization the most in these sectors. Moreover, transportation is currently shifting towards electrification; so, it is important to assess the sustainability of this deviation. Overall, the introduction of renewable energy in the context of a smart city is going to be considered. Renewable energy is obtained by resources that are not extinguishable; in fact, the advantage over energy coming from fossil fuels is that the natural endowment of fossil fuels is limited. Thus, for a type of energy to be included in this category, its source should be not depletable or at least be replenishable. The most common forms of renewable energy are wind, solar, hydropower, biomass, and geothermal. Their distinguishable characteristic is that their production of greenhouse gases and pollutants is less intensive than that of non-renewable resources. However, not all renewable energy is carbon-free, as in the case of biofuels and bioenergy; correspondingly, not all non-renewable energy is carbon-intensive, as a nuclear power plant does not emit any greenhouse gases, even if it relies on a scarce resource such as uranium [95]. Obviously, some renewable energy allows for decentralization, intended as the ability of single households to be ideally self-reliable, such as through the installation of solar cells or wind turbines. However, this is not the case for all renewable energy. Therefore, understanding how an energy system could work in a smart city and its linked challenges is paramount for the discussion.

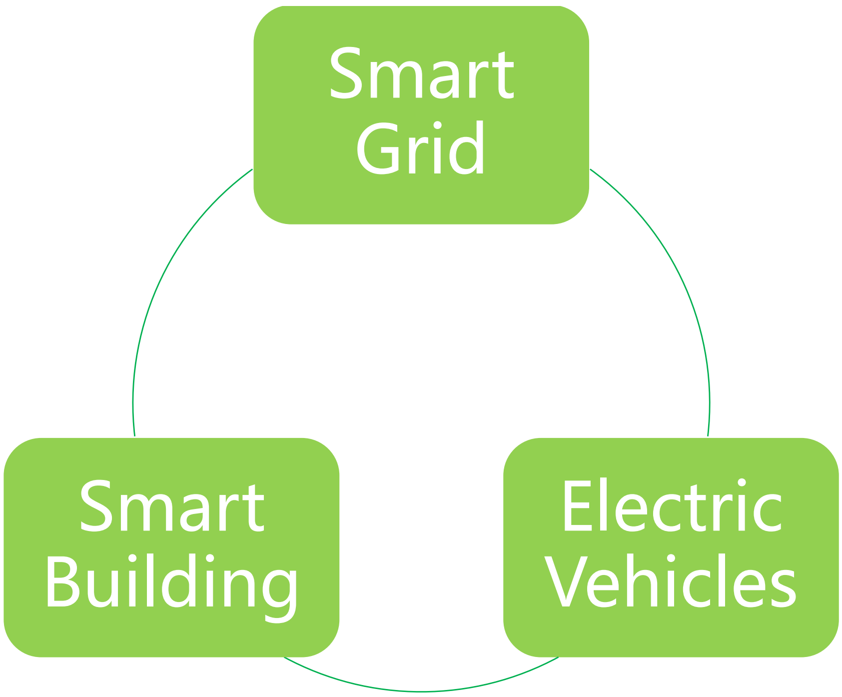

Figure 1. Energy-related elements of a smart city.

5.1. Smart Grid

The concept of a smart grid is stringently related to the introduction of fluctuating renewable resources and shifting the reliance away from fossil fuels, while, at the same time, keeping the demand and the supply balanced [96]. However, from a wider perspective, the typical core feature to identify in a smart grid is a bi-directional power flow, meaning that consumers are also producers of energy themselves, leaving behind the traditional role of passive users [97]. The main challenge that the development of smart grids faces is the grids themselves, as most of them were constructed to accommodate large fossil fuel-powered plants, delivering power in one direction only, to consumers [98]. An overview of a regular power grid is illustrated in Figure 2. Hence, three components are fundamental for this bi-directional flow; these are demand-side management, storage technologies, and real-time infrastructure management. Each of these components favors the integration of technological support. In particular, AI has been applied in four main areas: load forecasting, power grid stability assessment, faults detection, and security problems [28]. To clarify the meaning of the latter area, security problems may arise with the introduction of information technologies themselves into the electric grid as they can allow cyberattacks aimed at disrupting the normal, regular operations. As a result, AI applications have been devised to detect when these attacks are happening. In the context of a smart city, the development of a smart grid may be considered a fundamental basis for tackling the environmental issues and energy shortages that are becoming more and more common around the world, especially in Europe and Asia (for a timeline of the global energy shortage crisis, Bloomberg Green provides a detailed account of the most significant events, at: https://www.bloomberg.com/news/storythreads/2021-09-28/global-energy-shortage-why-is-everyone-talking-about-a-power-crunch, accessed on 2 May 2022). The question is whether AI can facilitate the transition to renewable resources, especially the ones of an intermittent nature (Table 3), and the reduction in energy consumption.

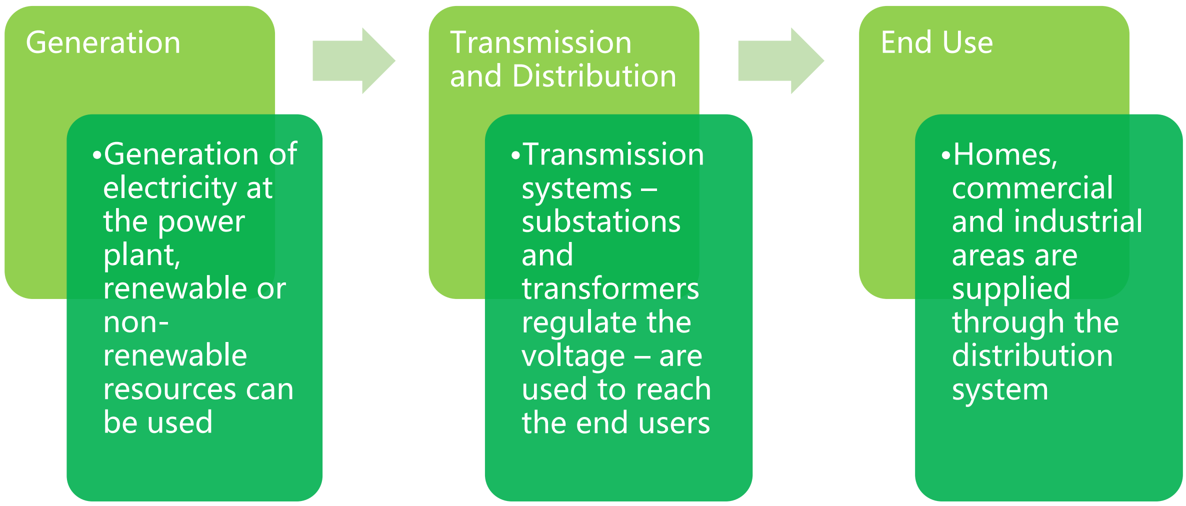

Figure 2. A simplified overview of the components of a power grid.

Table 3. Summary of the different types of renewable energy.

Type	Energy Source	Intermittent/Not Intermittent
Bioenergy	Plant and algae-based materials	Not Intermittent
Geothermal energy	Hot water below Earth's surface	Not Intermittent
Hydropower	Drop in flows of water	Not Intermittent
Marine energy	Waves, tides in flows of water	Intermittent
Solar energy	Solar radiation	Intermittent
Wind energy	Wind	Intermittent

One technique that has been used to match the demand for energy with the supply is variable pricing. For instance, an increase or decrease in the price is coordinated with an increase or decrease in the demand. Hence, at peak hours the price is higher as energy plants operate at near-maximum capacity, while in off-peak hours the price is reduced. In such a way, consumers are encouraged to use home appliances when the demand for energy is lower [99]. In fact, the demand response efforts are conceived to engage consumers by offering the financial incentive of cheaper electricity bills. The flexibility provided by such efforts also has the potential to meet the fluctuations of renewable energies and to facilitate their higher penetration [100]. In this scheme, AI-backed applications have been designed to support such practices. Lu et al. [101] have proposed an RL algorithm to balance the service providers' profit and the customers' savings to achieve the reliability of the power system. A promising area for demand response in which AI can be applied is the data centers [102]. In fact, one of the most important elements of a smart city is the vast stream of data that it should collect [34]. However, at the same time, the data collection and storage process could represent an environmental challenge for the development and expansion of such a city. Data centers are energy-intensive enterprises, estimated to have accounted for around 1 percent of worldwide electricity use in 2018 and whose efficiency is based on compacting together thousands of servers [103]. In 2021, it was predicted by Koot and Wijnhoven [104] that data centers would be likely to consume 2.13 percent of the global electricity available by 2030. On the matter of energy consumption, Crawford [105] has guarded against claims made by companies about being carbon neutral as it can be due to the purchase of carbon credits instead of the use of renewable resources.

From an environmental point of view, the sustainability of data centers is strictly connected to whether renewable or low-carbon resources are used to power their functioning. It is important to point out that excessive water consumption is a linked issue as water is not only used to cool down data centers, which in turn are also the major factor in energy consumption, but it is also indirectly used in electricity generation itself [106]. This is extremely relevant to the water scarcity related to climate changes as it has been reported that the entire supply of water on the planet, including snow and ice, has declined by 1 cm per year over the past two decades [59]. Even though steps towards the mitigation of these environmental issues have already been taken by the service providers and policy-makers [103,106], the optimization of energy consumption can further aid in solving this challenge. Li et al. [107] have proposed a DRL algorithm to optimize the cooling system of data centers and to reduce the cost related to it. A related real-life application of AI in data centers is the ML approach developed by DeepMind for Google, through which the amount of energy required for the cooling system was reduced by 40 percent in 2016 [108]. In 2020, it was reported that Google was collaborating with DeepMind to make the technology available to industrial enterprises [109].

Another technique to balance demand and supply is energy storage. Overall, there are many different types of storage systems, such as mechanical (e.g., flywheels), electrochemical (e.g., lithium-ion batteries), thermal (e.g., heat storage), or chemical (e.g., fuel cells) energy storage systems. However, they can be further divided into two categories based on their applicability. On the one hand, there are grid-scale applications suitable for bulk storage. On the other hand, there are demand-side applications, which are limited to localized areas. Demand-side storage is often associated with the on-site production of energy, as the case generally is with some forms of renewable resources, such as wind and solar. AI can be considered for a wide scope of applications in storage technologies. For instance, AI has also been applied to the design and testing of the storage systems themselves, as in the case of the material selection for lithium-ion batteries to maximize their autonomy [110]. In the framework of an electric grid with renewable resources, an algorithm has been developed to assess the right placement and sizing of a battery energy storage system as this should ensure better reliability and reduce power losses [111].

Similarly, Han et al. [112] have proposed an approach for the appraisal of the minimal power capacity of an energy storage to accommodate variability from high penetration levels of renewable generation. However, AI also has the potential to be applied to the infrastructure itself, as presented in the work of Ahmad et al. [113]. A problem that should not be overlooked in connection with energy storage systems is the one of potential cyber-attacks. More generally, the concept of the smart grid has been associated with the risk of cyberattacks given the expected dependence on the communication infrastructure to support the large amounts of data necessary for operations. Such attacks are expected to provoke significant damages; plus, the recovery process could require enormous investments, as analyzed by the World Economic Forum [114]. The first reported cyberattack on critical infrastructure was in 2010; the attack aimed to sabotage a nuclear power facility in Iran [115]. Another important event was the cyberattack on Ukraine's power grid in 2015; hackers were able to disable the control systems used to coordinate remote electrical substations, leaving people without power for several hours [116]. Commonly, the nature of cyberattacks can be either false data injection attacks (FDIA) or distributed denial of service. Whereas AI can be maliciously weaponized in cyberattacks [117,118] the technology also has the potential to represent a valuable solution to these issues in the near future [119]. To conclude, AI can aid in the transition to renewable energy but without becoming a source of high energy consumption itself. Hence, the principles of Green AI should receive recognition among policymakers for safeguarding the environment.

5.2. Electric Vehicles

Electric Vehicles (EVs) can be considered extremely important for the development of a smart transportation system, especially if the goal of tackling environmental concerns is acknowledged in the context of a smart city. EVs have been understood to be one of the solutions to the climate issues, as they do not have an internal combustion engine; instead, they are driven solely by one or more electric motors, which are powered by energy stored in the batteries. The batteries are charged by plugging the vehicle into an electric power source, meaning that the environmental impact of EVs is strictly connected to how electricity is generated in the first place. From this perspective, the successful adoption of EVs as a solution to greenhouse emissions is contingent upon the reliability of the energy system inside a city to accommodate the charging demand, particularly if the objective is to use renewable resources. Whereas the term EV tends to be used as a synonym for electric cars, it includes all the machines that can be used to transport people, such as motorcycles, trucks, buses, or trains. Thus, in the case where the entire transportation system of a city is converted to the avoiding of tailpipe emissions, the overall life-cycle emissions have to be recognized to understand whether EVs are a feasible and sustainable solution to environmental issues in the framework of a smart city. The concept of EVs has seen a resurgence in recent years, but its technology has been around for more than 100 years. The first electric car hit the market in 1890 in the United States and sparked a lot of interest given that it did not show most of the issues connected with steam and gasoline, such as a long startup time for the first and a lot of manual effort to drive for the latter [120]. A few years later, Henry Ford and Thomas Edison worked together to realize an affordable electric vehicle, but Edison's batteries, as strictly requested by Ford, an internal resistance which was too high to power such a vehicle in comparison with the lead–acid ones. However, the real demise of the electric car was due to the discovery of Texas crude oil, which provided a cheaper power option. Recently, as higher importance has been given to building and contributing to a zero-emissions future, EVs have emerged as one of the potential technologies that can help reach the goal. A wide commitment to shift to EVs has been undertaken by policymakers, such as the "Electric Vehicles Initiative", launched by Clean Energy Ministerial (CEM), and carmakers, as the pledge of General Motors summarized in "Our Path to an All-Electric Future". Considering that most cities worldwide suffer from air-quality problems, mostly due to motor vehicles and traffic congestion, EVs have been linked with the concept of sustainable, smart cities, as they surely solve at least the problems connected to tailpipe emissions. Indeed, the 11th Goal from "The 2030 Agenda for Sustainable Development" supported by the United Nations, which concerns the topic of cities, cites the importance of transport to reduce the gas emissions related to transport [121]. However, despite this benefit, the introduction of EVs can represent a double-edged sword. From this perspective, AI can have a critical role in the mitigation of all the issues connected to EVs. Since 2011, the patent applications to apply AI to EVs have sharply increased, especially to solve the shortcomings linked to the short driving range, such as the battery capacity and charging time [122]. This convergence is significant to understanding to what extent AI can contribute to rendering EVs more environmentally friendly, besides their absent tailpipe emissions. As the focus is on the energy systems, the first step is to analyze whether an increased number of EVs can be supported by current infrastructures and whether AI can aid the charging process thereof. The charging of an EV can be carried out either at a public or a home station, with the latter being the more popular of the two options [123]. Urban planning supported by AI, as with the system proposed by Flynn and Giannetti [124] to identify suitable properties for EV charging, could promote specific incentives to citizens living in areas apt for the installation of a private station. However, if the energy in an area comes from non-renewable resources, such as fossil ones, should the installation still be encouraged? The issue, in this case, is that an EV would still indirectly contribute to greenhouse emissions [27]. Whereas the same reasoning could apply to a public charging station, a further consideration of the effect of charging a fleet of EVs on the grid infrastructure is needed. One example of this situation is workplace charging, in which the issue relates to the assignment of the available resources fairly between all the EVs while avoiding overload [125]. The issue of possible overloading and the linked malfunction of the power grid could be additionally exacerbated by the uneven distribution of public stations. It has been stated that, on average, in Europe, there are 62 charging points per 100,000 inhabitants and in the United States, 37, on the same per capita basis, according to a report published on Reuters [126]. The limited number of charging stations can be an important barrier to the transition to EVs [127]. One solution could be identified in a similar ML system to the one proposed by Spuritha et al. [128], in which the data collected through the online booking of a charging station is used to forecast power consumption and accommodate the demand for desired charging for each customer. In a similar framework, it would be important to account for the different charging times between Level 1, Level 2, and Level 3 charging stations [129]. The first has a speed of adding around a range of five to eight kilometers per hour, the second of 19 to 129 km per hour, and the latter of 5 to 32 km per minute, which is the fastest one [130]. Level 1 stations may create bottlenecks in public stations and might be considered less suitable in the context of a city. In contrast, Level 2 charges approximately ten times faster, ensuring that an EV will be charged from two to four and a half hours, depending on the model's charge rate. Level 3 would be the most suitable, but investing in such fast-charging infrastructure may be improbable in places with low EV adoption as it could fail to be economically viable [131]. This means that congestion is not only directly connected to the number of charging points but also to the charge rate available at each one of them. However, as the number of charging stations may increase, there is still the risk that power grids may be inadequate to support the mass adoption of EVs [132]. Moreover, greenhouse emissions may be intensified by the higher energy demand. In this case, estimating and scheduling an optimal temporal distribution of charging events could be useful in reducing the environmental impact of electricity generation coming from non-renewable resources [133]. This would entail that EV owners should freely adhere to the timing schedule. Hence, it is likely that peak demand from charging will coincide with the peak in the domestic demand [134]. What has yet to be contextualized about simultaneous charging is that an increase in the energy network's load during peak hours can ultimately lead to a severe voltage drop [135]. Thus, the associated dissipation of energy, which results in the wasting of resources, should be considered counterproductive and undesirable to the environmental cause. The concept of vehicle-to-grid could help alleviate this probable issue; in such a manner, when demand is high, the EVs plugged into the grid can act as a support mechanism by storing and dispatching energy from their own batteries [136]. Hence, an aggregation of multiple EVs can have a significant impact as a generation/storage device, which can allow the owners to economically offset the charging costs by selling surplus energy back to the grid operator [137]. A useful RL method to optimize this practice has been proposed by Najafi et al. [138], in which the goal has been to allow customers to purchase energy for their EVs when the price is low and sell it back when it is high only if enough has been stored for personal use. Whereas such as a technique would support an adequate aid to the energy grid, it is necessary to account for the deterioration of the batteries in the EVs participating in the vehicle-to-grid system [139]. This is of particular importance as the disposal of lithium-ion batteries is not always environmentally friendly, especially in landfill sites, where contamination of the soil can happen. It has been reported that only around five percent of the disposed batteries are actually recycled [140]. Additionally, the materials needed for the construction are considered scarce resources, and mining lithium hurts the environment, such as by water contamination [141]. Hence, a faster deterioration of the batteries may be an undesirable side effect of the vehicle-to-grid system. Even if EVs do not produce tailpipe emissions, their manufacturing process is the one that produces the higher greenhouse emissions, which can account for 11 percent to 23 percent of the total lifecycle emissions among all the types of vehicles [142]. If the indirect environmental impact due to the use of non-renewable resources in the energy grid is also considered, the element of the EV inside the context of a smart city should be promoted only if there are corresponding policies to reduce the overall greenhouse emissions. Whereas electrification of public transportation is up to the local government, it is important to consider that private owners play an important part in the full process. Hence, the advantages and disadvantages of EVs (Table 4) can play a major role in wider adoption.

Table 4. Summary of the major advantages and disadvantages related to EVs.

Strengths	Weaknesses
Electricity has a lower cost than fuel	High upfront costs
No direct carbon emissions	Long charging time
Reduced noise pollution	Shorter autonomy range
Less maintenance for battery and motor	Expensive to purchase a new battery
Possibility of home charging station	Limited number of charging points

5.3. Smart Buildings

The concept of a smart building is intrinsically connected with energy efficiency, given that it can be considered as support towards the objective of the long-term sustainability of resources. As it has been estimated that residential and commercial buildings are responsible for over one-third of energy-related greenhouse emissions globally, the major mitigation strategy has been identified with the reduction in their overall energy consumption [143]. AI is expected to play an important role by potentially monitoring and managing the use of energy, which in turn could ease the integration of renewable energy and independent power production [144]. Thus, the smart building is an important element of the smart grid as it allows for the efficient demand-side management of energy, which would be not possible otherwise. A comparison between a conventional grid and a smart grid is provided in Table 5. On-site energy production can be conducted only through four resources: wind, solar, geothermal, and biomass [145]. It is important to mention that geothermal energy is limited to areas in which there are reservoirs of water of a temperature that ranges from 20 °C to 160 °C, and biomass energy, which, even if it is considered a renewable resource, directly produces greenhouse emissions. Thus, these two forms of energy are not going to be considered in a general framework of a smart city and buildings. Specifically, the issues with integrating wind turbines and solar panels are going to be presented to understand to what extent the independent production of energy could be considered a solution to shortages and greenhouse emissions in cities. In this context, an assessment of whether AI can aid efficiency is going to be made.

Table 5. Smart grid vs. Conventional grid.

Smart Grid	Conventional Grid
Bi-directional distribution	One-directional distribution
Decentralized generation	Centralized generation
Consumers are also producers	Passive consumers
Back-up in case of emergency	No customer-owned storages
Sensors to assess the stability	Minimal use of technology
Quick restoration after disruption	Disruption can create domino effects
Automated off-peak purchase	Electricity rates depend on demand
Possibility for complete independence	Strict reliance on the grid
Smart meters for energy saving	Meters only show the consumption

Starting from solar energy, the most common way in which such energy is produced is through the use of solar panels. Their installment is contingent upon solar exposure, and a lack of appropriate sunlight determines the unviability of the panels. When they are placed on top of the building, it is also necessary that the roof conditions are good enough that they do not require a short-term replacement [146]. Otherwise, solar energy systems can be shared among different buildings as solar panels are placed in an off-site array. AI can aid in identifying areas in which the predicted generation of solar energy [146] is enough to favor the installation of solar panels. Patel et al. [147] have indeed proposed an AI-backed approach in which the predicted energy generation of a given residential area could be used to recommend the installation of solar panels, to reduce in such a way the gap between demand and the supply of energy. At this point, it is important to consider the upfront cost of installing solar panels because part of the transition to sustainable solutions can be expected to be in the hands of the people themselves. Even if it is becoming more affordable, installation is still a significant expense that not every household or community would be willing to pay [148]. The same reasoning applies to wind turbines. Wind turbines, like solar panels, cannot be installed wherever, as they require an average wind speed of around 6 m per second to function properly [149]. They work better in rural areas, as there should not be any obstructions such as trees or tall buildings; thus, a residential application in the context of a city is very constrained [150]. However, when solar and wind power are integrated into a building, AI applications can be a great support for the proper functioning of the energy system. Nabavi et al. [151] have proposed an approach that forecasts the energy demand and supply to reduce the imported electricity from the grid, which should result in overall cost minimization. In this way, the scheduling of when energy should be stored, exported, or imported from the grid is optimized. One thing that can emerge is the importance of energy storage in the framework of a smart building to support renewable resources. Adding a storage system is an additional expense that people should independently decide to further undertake [152]. An energy market based on an AI-backed platform, such as the one proposed and discussed by Xu et al. [153], would offer the advantage of exchanging energy, as well as buying and selling storage capacity. This would alleviate the upfront, lump-sum investment needed to own a storage battery. However, surplus energy can be injected back into the grid even where there is no storage battery. In this case, households are still reliant on the energy grid, but they can exchange back renewable energy and receive a monetary compensation—in areas where this is possible. Even though solar power does not generate air pollution or greenhouse gases, the manufacturing of a photovoltaic system is estimated to use the equivalent amount of energy that the system itself can produce within one to four years from its installation [154]. Moreover, most photovoltaic systems have operating lives of up to 30 years, but an appropriate recycling practice has not been established yet as the panels contain small amounts of valuable materials [155]. This may result in the disposal of solar panels in landfills, especially in countries where there is a lack of regulation. Similarly, wind turbines have a limited lifespan of around 20 years, and the recycling of their components is not an easy, cost-effective process [156]. This can represent another hurdle to the adoption of renewable energy in a smart city. However, renewable resources are not the only way to solve the problems of energy-related emissions in cities. Energy-efficient choices supported by AI may also be considered be a less radical fix to this issue. An AI-backed prediction model based on the occupant density and its related greenhouse emissions for appropriate energy management, as envisioned by Chen et al. [157], could be one solution. Moreover, an AI application similar to the one proposed by Bagheri et al. [158], which regulated the heating system of a building to improve energy savings, could represent another viable solution. This method has been shown to achieve energy savings rates of at least 67 percent during the months of March and April. However, two shortcomings are also coming with the smart thermostat. The first is that people may not fully understand the functioning of an automated energy management technology and might, consequently, involuntarily interfere with it [159]. The second is that such a system could not force consumers to conform to its energy-saving actions as they could intervene by shutting it down. Thus, if a consumer wants to turn on the air conditioning during a warm day, resulting in high energy consumption, the system cannot prevent such action. He et al. [160] have tackled this problem by using a virtual assistant to nudge consumers into taking energy-savings actions. Still, it is up to consumers to adhere to the suggestions.

6. Cases of AI Applications in Smart Cities around the World

Whereas the potential of AI has been largely discussed up to now, in the next sections, a few cases will be analyzed to appraise how AI is really contributing to cities around the world.

6.1. Taiwan's Streetlights

The government of Taiwan has recently pledged to focus on research and development in green energy, smart grids, and energy storage equipment to cut carbon emissions [161]. However, an initial effort towards the reduction in carbon emissions was to apply AI to streetlights to reduce energy consumption. In such a way, cameras were combined with smart streetlights to help identify the flow of people and traffic. Hence, if there is no movement for more than 10 min, the streetlights automatically darken by 50 percent. Reportedly, this solution has helped in saving electricity by 12 percent in the Qingpu area of Taoyuan City, as announced by a press release from Smart City Taiwan [162].

6.2. Barcelona's Smart Building

Barcelona has long engaged in initiatives aimed at the evolution towards becoming a smart city. The city is widely considered among the pioneers of this trend. In 2015, Forbes proclaimed Barcelona as "the top smart city" in the world [163]. More recently, in a pilot project, a building that hosts a therapeutic and educational center for young people located in the Sarrià-Sant Gervasi district has been equipped with solar panels and energy storage. An AI-backed management system, which takes into account a multitude of factors, such as weather forecasts, energy market prices, and the anticipated demand, has been used to coordinate the charge and discharge of the storage. In this way, the energy management was optimized to reduce the carbon footprint. It has been reported that the center has been able to achieve a 20 percent self-sufficiency rate and a 17 percent drop in greenhouse emissions, as reported by the Barcelona city council [164].

6.3. Summerside's Smart Grid

The city of Summerside, which is located on the Canadian Prince Edward Island, has announced that it has the first end-to-end AI-optimized smart grid in North America [165]. The AI-backed software has the scope to predict the energy need in order to improve the efficiency of the local renewable resources. Thus, by forecasting the demand an hour ahead, the decision to purchase additional energy should be optimized to avoid losses. The efficiency of the software has yet to be officially assessed, and its functioning is still being monitored by the local authorities [166].

6.4. Ottawa's Smart Charging

A new pilot project has been announced in the city of Ottawa to meet the growing energy needs for charging EVs [167]. The project is going to be realized by BluWave-ai, the same company that has developed the software for the city of Summerside in the previous case, along with Hydro Ottawa, the Independent Electricity System Operator (IESO), and the Ontario Energy Board (OEB). It is named "EV Everywhere" and the objective is to employ AI to create an online service for EV owners to smooth out demand peaks and take advantage of lower-cost energy at off-peak times. This should result in an optimal dispatch of energy, which, in turn, should support the high forecasted increase in demand due to the higher adoption of EVs. It would be important to understand the efficiency of this pilot project, when realized, to assess the potential of AI-backed smart charging in the context of a city.

6.5. Singapore's Smart Office

Singapore is among the cities at the forefront of the evolution towards becoming a smart city. With the help of Spanos, who is a professor at UC Berkeley, an AI-backed thermostat was developed to regulate the temperature inside an office space [168]. The office has been equipped with sensors to detect humidity, light, temperature, and CO_2 concentration. Furthermore, Wi-Fi has been used to triangulate employees' locations by detecting their phones. If the workers become too hot or too cold, they can use an app to regulate the temperature. The goal is for the AI system to learn the different preferences and tweak the environment to suit them. At the same time, it should nudge the workers towards energy-saving behavior. Whereas the expectations were to substantially cut energy consumption, the results from the trial have yet to be publicly shared.

6.6. Discussion and Further Analysis

As it is possible to notice, the introduction of AI in the energy-related components of smart cities is still in a developmental phase. A limited number of pilot projects can be observed, and the results are closely connected to the controlled context in which they take place. This gap between the potential of AI and its actual real-life applications should be taken as an opportunity to avoid the drawbacks that have been comprehensively presented in Section 4.

To extend the discussion of the topic of AI in relation to smart cities and sustainability, there is another promising area in which the technology is expected to contribute considerably. Autonomous Vehicles (AVs) have been predicted to lower the greenhouse emissions from transport, through services such as automated taxi services [169]. However, how the adoption of AVs will play out is surrounded by many questions. Cugurullo et al. [170] have pointed out that AVs could align with sharing services, allowing for urban spaces to be remodeled to accommodate cycling lanes, gardens, and public places, but they could also increase the demand for private vehicles. An important perspective has been provided by Acheampong et al. [171]. From their study, it has emerged that people who prefer owning their vehicles are also more likely to want to own an AV. Hence, there is a strong possibility that current, unstainable urban models will not be changed just with the introduction of AVs. This further calls for the need for an efficient charging infrastructure for the adoption of EVs, to which AI should be conscientiously applied.

Aside from the possible negative side effects of AI applications discussed in relation to environmental issues, other challenges are worth analyzing. Despite the issue of data privacy, which has been previously discussed in this paper (Section 3), another negative externality of AI is related to excessive data generation. One insight provided by Acemoglu et al. [172] is that this problem is still connected to privacy because when data sharing by other users is perceived as compromising the information of another individual, this individual has less incentive to value privacy. This is rooted in the fact that data of a subset of users may also reveal information about other users, and, in such a way, excessive data are generated, for which the market price tends to be correspondingly low. This easy access to personal data can have many downsides. One of the most discussed issues in relation to societal impacts is the one of misinformation and targeted manipulation. Cinelli et al. [173] have analyzed the effects of feed algorithms as they are based on personal preferences and attitudes. They have found that social perceptions and the framing of narratives have changed with social media, and groups created around shared narratives tend to be extremely polarized, leading to the proliferation of misinformation.

One example of such a tendency is the propagation of conspiracy theories, which are strictly linked to economic inequality in today's society and to intergroup hostility [174]. On this matter, a wider economic disparity has been connected with the introduction of AI applications [175]. The prediction of mass unemployment appears to be too negative a scenario in the light of the study by Hunt et al. [176], in which it has been evaluated that job creation is just as likely as job destruction. However, it has been hypothesized that AI may change workers' access to economic opportunity even more starkly than the redistributions generated by past waves of technological progress [177]. To close the circle, Dauvergne [178] has related this problem of income inequality to environmental injustice, claiming that wealthier individuals have been increasingly consuming a greater share of the world's natural resources. Yet, the negative effects of this increased consumption are unfairly shared among the world population.

Smart cities could reasonably be associated with a similar argument based on the increasing income inequalities due to more opportunities being available for highly qualified individuals. However, a preliminary, empirical finding from the work of Caragliu and Del Bo [179] appears to support the opposite view.

7. Results and Conclusions

In a smart city, governance is a fundamental asset as policies improve the quality of life of the citizens, enhance leadership, protect the environment, and support local economies. However, one of the challenges in planning effective practices in a smart city is uncertainty, an issue mitigated by collecting information from heterogeneous sources and developing proper algorithms dedicated to their analysis. The outcome of this process represents a valuable resource to support decisions on a rational basis.

However, the cost of this operation should not be neglected, as the hardware and the data storage facilities adopted by software can have a strong impact from the energy point of view and, ultimately, on the environment. With regard to information processing, the bottleneck—both in terms of performance and energy consumption—is typically located in historical, centralized IT architectures, where a main server, which is often scalable only at the risk of very high cost, elaborates the entirety of the incoming data. Following the diffusion of the internet on a global scale, the usual textual representation of information has passed through numerous transformations, becoming visual, vocal, and finally iconographic, making its interpretation more complex. The exposure of the individual to the web and, more specifically, to an entirely wired smart city where whatever information can be measured is potentially collected and where cameras monitor the flow of traffic or even the trajectories and movements of pedestrians to prevent safety issues, presents many concerns in terms of privacy and freedom. A potential side-effect of over-information may result in algorithms built to nudge smart citizens—to preserve water and energy or to take public transport to reduce pollution—that are barely effective, due to a skepticism about the way information is circulated and handled by local authorities. Cyberattacks and the undisciplined circulation of data about health are other sources of concern.

Firstly, more rational IT architectures have been adopted. They are based on distributed networks, where small nodes with limited processing capacity are interconnected. Furthermore, specific units act as workload balancers, optimizing energy consumption by distributing the data stream over the nodes in a weighted manner. Secondly, with regard to the privacy concerns, the European General Data Protection Regulation (GDPR) poses strict directives on data retention, data confidentiality, and data consent. Similar regulations are discussed by the California Consumer Privacy Act (CCPA), Brazil's Lei Geral de Proteção de Dados (LGPD) and South Africa's Protection Of Personal Information (POPI). In a similar manner, the EU has recently adopted the recommendation on a European Electronic Health Record exchange format, though the threat of cyberattacks remains potentially harmful.

More concerns revolve around AI and, specifically, the cost of deploying it pervasively as this might result in further controversies, i.e., (i) job losses, due to an uncontrolled replacement of working activities considered repetitive and barely motivating; (ii) populism, deriving from undetected bias in datasets used to train algorithms that are supposed to guide the individual in taking choices; (iii) ethical concerns, for example when the individual has no role in decisions typically drawn by an algorithm; and, finally, (iv) lawful issues, related to the lack of a formal definition of AI as a legal identity. All these aspects can be mitigated by the definition of proper polices aiming at (i) supporting and encouraging AI-inclusive education programs; (ii) implementing algorithms alleviating and reducing bias in datasets, (iii) enforcing actions based on cooperation between humans and AI software; and (iv) pursuing a robust definition of legal personhood defining the rights and duties of AI software.

The results provided by the research indicate that both data and AI can be legitimately added to the pillars of smart cities.

Recently, there has been a shift in the perception of the concept of a smart city, and scholars are recognizing the importance of environmental awareness in its development. From this perspective, the energy-related components (smart grid, electric vehicles, and smart buildings) play a fundamental role in the reduction in the ever-increasing greenhouse emissions produced by cities around the world. With regard to the proposed two pillars, information is crucial to design adequate nudging techniques. From this study, it has emerged that not all the nudging techniques are effective when the target is to reduce energy consumption. However, these specific nudges are already endowed with a significant degree of personalization, with targeting being inevitable as single households or neighborhoods are usually the addressees of such methods. This allows for the introduction of AI-backed nudges—also referred to as hypernudging. Yet, their success is closely linked with the personal propensity of each individual. For instance, a free-riding tendency may compromise their impact, resulting in highly context-dependent results.

Continuing the discussion surrounding AI and the energy-related components, these components themselves can be enhanced with the technology. The evolution towards a smart grid has been strictly associated with the introduction of renewable resources and on-site production that allows consumers to have an active role. AI applications can be of crucial support but should not result in an additional source of high energy consumption. Otherwise, a vicious circle may be inadvertently created, with AI instead becoming an additional environmental issue. The electrification of vehicles is linked with a functioning smart grid. The introduction of electric vehicles should be coupled with the one of renewable energy, or it can result in indirect emissions due to carbon-intensive resources. AI can act as an aid in localizing areas where charging points can be positioned, scheduling charging events and participating in the vehicle-to-grid system. However, negative effects should be considered in all these applications, including the use of carbon-intensive energy, the risk of overloading, and the deterioration of batteries made with scarce materials such as lithium. Smart buildings are another important element of the smart grid, as they allow for the efficient demand-side management of energy. For the optimal management of the on-site production of renewable energy, AI applications have shown to possess promising results. Forecasting the energy demand and supply can reduce the imported electricity from the grid, both when an energy storage system is present and when it is not. Nevertheless, the installation of solar panels, wind turbines, and storage technologies can be a considerable investment that cannot be widely embarked upon. Renewable resources are not the only way to solve the problems of energy-related emissions in cities. AI-backed energy management aimed at reducing consumption is a viable solution. However, what must be considered is that people can easily interfere with it.

The results coming from the real-life cases show that AI applications for energy-related components are still in a developmental phase. Hence, there is no strong evidence that points against the adoption of AI in this component of a smart city. This should be taken as an opportunity to avoid the drawbacks that are likely to emerge with wider adoption.

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