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Perspective

Green Artificial Intelligence: Towards an Efficient, Sustainable and Equitable Technology for Smart Cities and Futures

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Abstract: Smart cities and artificial intelligence (AI) are among the most popular discourses in urban policy circles. Most attempts at using AI to improve efficiencies in cities have nevertheless either struggled or failed to accomplish the smart city transformation. This is mainly due to short-sighted, technologically determined and reductionist AI approaches being applied to complex urbanization problems. Besides this, as smart cities are underpinned by our ability to engage with our environments, analyze them, and make efficient, sustainable and equitable decisions, the need for a green AI approach is intensified. This perspective paper, reflecting authors' opinions and interpretations, concentrates on the "green AI" concept as an enabler of the smart city transformation, as it offers the opportunity to move away from purely technocentric efficiency solutions towards efficient, sustainable and equitable solutions capable of realizing the desired urban futures. The aim of this perspective paper is two-fold: first, to highlight the fundamental shortfalls in mainstream AI system conceptualization and practice, and second, to advocate the need for a consolidated AI approach—i.e., green AI—to further support smart city transformation. The methodological approach includes a thorough appraisal of the current AI and smart city literatures, practices, developments, trends and applications. The paper informs authorities and planners on the importance of the adoption and deployment of AI systems that address efficiency, sustainability and equity issues in cities.

Keywords: artificial intelligence (AI); green AI; sustainable AI; responsible AI; ethical AI; explainable AI; AI regulation; green sensing; sustainable development goals; smart cities

1. Introduction: AI in the Smart City Context

The second digital and fourth industrial revolutions cultivated an innovation culture for the flourishing of many technological developments and breakthroughs [1,2]. For instance, the field of artificial intelligence (AI)—defined as algorithms that mimic the cognitive functions of the human mind to make decisions without being supervised [3]—has undergone remarkable exponential growth over the last couple of decades [4]. Today, AI is undoubtedly an in-trend, disruptive technology with countless applications, and even more prospects, for all industry sectors and areas of life—ranging from health to agriculture, engineering to finance, gaming to transportation, and so on [5]. Besides this, AI is one of the fundamental drivers of the global smart city movement [6].

Smart cities are widely seen as locations whereat digital technology and data are widely applied to generate efficiencies for economic growth, quality of life, and sustainability [7]. Today, in many urban policy circles and debates, concerning smart city transformation, AI has become a subject of debate, particularly among urban policymakers and planners who search for technocentric solutions to alarming urbanization problems [8]. This popularity is due to the increasing recognition of technocentric solutions as a potential panacea to the complex and complicated urbanization challenges—ranging from quality of life to climate change, and safety and security to mobility and accessibility [9]. The effective use of big data, AI-powered smart urban technologies and platforms is predicted to benefit urban infrastructure and service efficiency, and to address or at least significantly ease these challenges [10,11].

As stated by Wang and Cao [12], technological advancements have generated an era wherein large volumes of data—i.e., big data—are collected via smart sensors deployed in cities, and are made available via various commercial and public channels. Due to the recent advances in AI techniques and ubiquitous computing, these data now feed into the services that improve quality of life, city operation systems, and the environment. In the context of cities, AI has various applications in areas that aim to create efficiencies in urban infrastructure and services [13]. The following are among the most prevalent AI-powered examples:

- Automated algorithmic urban decision-making (e.g., identification and penalization of traffic offences and tax evasions through smart sensors and machine learning-based data analytics) [14];
- Automated urban infrastructure assessment (e.g., monitoring urban infrastructure health through automated aerial mapping and deep-learning characterizations) [15–17];
- Autonomous urban post-disaster reconnaissance (e.g., detecting disaster damage and impact through synergistic use of deep learning and 3D point cloud features) [18];
- Autonomous and connected urban mobility (e.g., offering increased urban mobility through shared autonomous vehicles and autonomous shuttle bus fleets) [19,20];
- Urban descriptive, diagnostic, predictive and prescriptive analytics (e.g., gathering and interpreting urban air pollution data to describe what is the pollution level, why it happened, when it may occur again, and actions to influence future desired outcomes) [21];
- Urban security, safety, rescue and maintenance robots (e.g., emergency services operating rescue robots in risky and dangerous environments, such as natural disaster events, mining accidents and building collapses and fires) [22];
- Urban service agent chatbots (e.g., offering improved customer experiences with reduced waiting times to access services in different languages related to taxation, health services, public transport, family services, job opportunities and so on) [23].

In an attempt to generate the required efficiencies and proficiencies, many governments across the globe have started to deploy various AI system initiatives at the national, state and local levels [24,25]. The following are among the most common AI-driven applications [26]:

- AI process automation systems;
- AI-based knowledge management software;
- Chatbots/virtual agents;
- Cognitive robotics and autonomous systems;
- Cognitive security analytics and threat intelligence;
- Identity analytics;
- Intelligent digital assistants;
- Predictive analytics and data visualization;
- Recommendation systems;
- Speech analytics.

Despite the efforts made to adopt and deploy AI in the public sector, almost all of these initiatives have either struggled, failed, or lacked the adequate potential to generate ethical, responsible and sustainable solutions [27,28]. This is also the case for the smart city domain—the existing purely technocentric or algorithmic AI perspectives could not play a prominent role in smart city transformation [26]. Toronto Sidewalk, Masdar and Songdo are among the major smart city initiatives that have resulted in project cancellations or failures in living up to their smart urban future promises [29].

The main reason behind this failure is that AI system adoption practices are heavily technologically determined and reductionist in nature, and do not envisage and develop long-term, ethical, responsible and sustainable solutions [30]. Most government AI approaches have also overlooked urban, human and social complexities; subsequently, this has created conditions for new forms of societal control, and boosted inequality and marginalization among the layers of our societies [31]. Thus, the current practice of AI has generated as many constraints as prospects, where, at times, the constraints outweigh the prospects [32].

Against this backdrop, this perspective paper highlights the fundamental shortfalls in current AI system conceptualization and practice, and points to a novel approach—i.e., green AI that also accommodates green sensing—that moves away from short-term efficiency solutions to focus on a long-term ethical, responsible and sustainable AI practice that will help build sustainable urban futures for all through smart city transformation. Here, we note that, as this is a perspective piece reflecting the authors' opinions and interpretations of the topic, the methodological approach of the paper is not systematic; rather, the paper uses the literature to support the claims and views related to AI and smart city discourses, practices, developments, trends and applications.

2. Prospects and Constraints of AI for Smart City Transformation

The utilization of smart and innovative digital technologies has become a common approach to tackling urban crises—whether they are related to climate, pandemics, natural disasters or socioeconomic factors [33,34]. In recent years, advancements in AI—as one of the most prominent technologies of our time, with significant implications for our economy, society, environment and governance—have resulted in invaluable opportunities for cities to increase their infrastructural efficiencies and predictive analytic capabilities, and hence, to a degree, to improve the quality of life and sustainability in cities under the smart city brand [35]. According to Ullah et al. [36], today, AI is rapidly becoming a critical smart city element that helps in achieving necessary efficiencies and automation in order to deliver urban infrastructures, services and amenities.

Especially when coupled with other smart urban technologies, AI applications—e.g., chatbots and virtual agents, cognitive robotics and autonomous systems, cognitive security analytics, expert systems, identity analytics, intelligent digital assistants, knowledge management systems, predictive analytics and data visualization, process automation systems, recommendation systems, speech analytics, threat intelligence—provide new capabilities and directions for our cities, such as building the next generation smart cities, i.e., the "Artificially Intelligent Cities" of the future [37]. There is a vast array of literature on the prospects of AI for smart cities [38].

Nonetheless, as much as creating benefits—for instance, generating operational infrastructure or service efficiencies—AI technology also involves substantial risks and disruptions for cities and citizens, through the opaque decision-making processes and the privacy violations that are related to it; e.g., automating inequality, generating algorithmic bias due to bad or limited data and training, removing or limiting human responsibility, and lacking an adequate level of transparency and accountability [39]. Additionally, in comparison to the other technologies, AI involves some unique data-related challenges that include data acquisition, the large volume and the streaming of data, heterogeneous data, complex dependencies among the data, noisy and incomplete data, distributed data storage and processing, training data, and data privacy [12].

Some examples of AI mishaps that impact society, and that also diminish public trust in the AI solutions implemented as part of smart city projects, include, but are not limited to, the following:

- AI misdiagnosis of child maltreatment and the prescription of inappropriate solutions in Pittsburgh, PA, USA [40];
- Amazon's AI recruiting tool, which took biased decisions towards women [41];
- Bias towards people of color in the decisions made by AI algorithms used in US hospitals [42];
- Clearview AI's scandalous facial recognition image database developed with images from social media, which got hacked in 2020, leaving citizens of democratic countries with privacy threats, and citizens of autocratic regimes under a situation akin to an Orwellian nightmare [43];
- The malfunctioning of the Australian government's automated debt recovery program, called Robodebt, resulting in a scandal, as it had unlawfully taken AUD 721M from over 400,000 Australians [44].

One of the main reasons behind the failure of AI systems relates to the development and integration stages of AI in urban and public services. Pasquinelli [45] linked the underlying issues of AI—or in broader terms, how machines learn—to the development of AI systems when operators engage in training data, learning algorithms and model application stages. In these stages, operators could encounter three types of bias, namely:

- Just-world bias (e.g., a cognitive bias that assumes people get what they deserve, leading to failures in helping or feeling compassion for others or disadvantaged groups, such as poor or homeless people);
- Data bias (e.g., an error caused by certain elements of data being more heavily represented or weighted than other elements, leading to wrong decisions or inequity issues—such as for women, people of color or minorities);
- Algorithmic bias (e.g., a lack of fairness, originating from the output of an algorithmic system, with consequential unfavorable decisions, actions or externalities—such as a credit score algorithm denying a loan).

When an AI system containing such bias is integrated with an urban or public service, the failure of the service, or dissatisfaction with the service, is inevitable [46].

The growing concern over negative AI externalities and service failures, particularly in smart cities, proves the need for more ethical and regulated AI systems [47]. Subsequently, in recent years, attempts to provide a more holistic perspective on AI have resulted in a number of new AI conceptualizations [48]. These include "responsible AI", "ethical AI", "explainable AI", "sustainable AI", "green AI" and the like, the aim of which is to ensure the ethical, transparent and accountable use of AI applications in a manner that is consistent with user expectations, organizational values, environmental conservation and societal laws and norms [49]. It is also argued that such renewed approaches to AI will help maximize the desired smart city outcomes and positive impacts for all citizens, while minimizing the negative consequences [50].

3. The Green AI Approach for the Flourishing of Humans and the Planet

The effects of human activity—e.g., unsustainable and rapidly growing populations, urbanization, industrialization and consumerism—since the industrial revolution of 1850s, and particularly during the last five decades, have taken their toll on the environment [51–53]. As presented by Hunter and Hewson [54], the most catastrophic threats humanity is facing today include the following:

- Chemical pollution of the earth system, including the atmosphere and oceans;
- Collapse of ecosystems and loss of biodiversity;
- Decline of natural resources, particularly water;
- Global warming and human-induced climate change;
- Human population growth beyond the Earth's carrying capacity;
- National and global failures to understand and act preventatively on these risks;
- Nuclear weapons and other weapons of mass destruction;
- Pandemics of new and untreatable diseases;

- Rising food insecurity and failing nutritional quality;
- The advent of powerful, uncontrolled new technology.

Among these threats, "national and global failure to understand and act preventatively on these risks" is the most important. This is the incapability of the governments [55] and the public [56] to understand and take actions against threats that are most likely to, or definitely, lead to a catastrophe. This issue is the root cause of the failure of AI solutions—even if they target sustainability [57]—as they are mainly used to improve business efficiency and economic productivity in our cities [58] rather than actually tackling the aforementioned global threats that are mostly anthropogenic in origin [59].

The flourishing of humankind over the last 10,000 years in the Holocene is a consequence of the planet's beneficial conditions, that is, the perfect climate and ecosystem [60]. As such, investigating the ways in which AI can help establish conditions in which humans and the planet can thrive in the Anthropocene has been the subject of much recent scholarly work [61].

For example, Vinuesa et al. [62] explored the role of AI in achieving the UN's sustainable development goals (SDGs). Their study found that "AI may act as an enabler on 134 targets (79%) across all SDGs, generally through a technological improvement, which may allow to overcome certain present limitations. However, 59 targets (35%, also across all SDGs) may experience a negative impact from the development of AI". In another study, Gupta et al. [63] assessed whether AI is an enabler or an inhibitor of sustainability, measured via SDGs. Their study disclosed that "when SDGs related to Society, Economy, and Environment were analyzed, it was observed that the Environment category has the highest potential, with 93% of the targets being positively affected, whereas Society has the largest negative effect with 38% of the targets exhibiting a negative interaction with AI".

Likewise, Goranski and Tan [64] examined the role of AI in accelerating the progress of SDGs. Their investigation revealed that "AI can generate data for more intelligent targeting of intervention, reduce waste and losses in production and consumption, create new applications that will transform entire industries and professions, and provide the necessary improvements in connectivity and cost reductions that brings the benefits of the rapid pace of technological development to many people worldwide". While AI represents an opportunity for achieving the SDGs, as stated by Dwivedi et al. [65], an AI-supported delivery of SDGs will "require significant investment from governments and industry together with collaboration at an international level to effect governance, standards and security". Figure 1 shows the 17 SDGs.

Additionally, in recent years, we have witnessed an increase in academic literature reporting the outcomes of AI technology applications for social good, and in tackling social and environmental issues [66]. The environmental areas in which AI applications are utilized range from air pollution monitoring [67] to wastewater treatment [68], from endangered species protection [69,70] to climate change detection [71], from natural disaster prediction [27] to ecosystem service assessment [72], and other applications in environmental sciences [73].

Figure 1. Sustainable development goals [74]. Source: https://www.un.org/sustainabledevelopment/news/communications-material/ (accessed on 9 August 2021).

While the existing and potential benefits of AI for the environment have been presented in the abovementioned studies, said studies also underlined the critical importance of addressing the risks involved. For instance, studies emphasized the critical importance of:

- Being supported by the necessary regulatory insight and oversight for AI-based technologies to enable sustainable development, and avoid gaps in transparency, safety and ethical standards [62];
- Going beyond the development of AI in sectorial areas, so as to understand the impacts AI might have across societal, environmental and economic outcomes [63];
- Offering a constructive, rather than optimistic or pessimistic, outlook on AI for promoting desired sustainable outcomes [75].

The most common negative effects of AI on the environment include increases in electricity usage (computation and transmission power consumption) and the resulting carbon emissions, along with errors in critical decisions due to user and data bias [76–78]. Given that global technology uptake is growing at an exponential rate, the impact of these externalities is expected to be immense [79]. Just to give an example, cryptocurrency mining in recent years has led to increased energy consumption globally.

As stated by Cuen [80], the bitcoin electricity consumption index of the University of Cambridge indicates that "bitcoin miners are expected to consume roughly 130 Terawatt-hours of energy (TWh), which is roughly 0.6% of global electricity consumption. This puts the bitcoin economy on par with the CO_2 emissions of a small developing nation like Sri Lanka or Jordan".

These undesired externalities call for a sustainable approach to AI that adopts a green-based technological perspective, including switching to a sustainable AI infrastructure [81–85]. In their study on the climate cost of global computation, Dobbe and Whittaker [86] made the following recommendations for tech-aware climate policy and climate-aware tech policy:

- Account for the entire tech ecosystem;
- Address AI's impact on climate refugees;
- Curb the use of AI to extract fossil fuels;
- Integrate tech and climate policy;
- Make non-energy policy a standard practice;
- Mandate transparency;
- Watch for rebound effects.

Making AI green and sustainable, i.e., the green AI approach, requires a bias-free (besides a reasonable environmental bias or positive discrimination), inclusive, trustworthy, explainable, ethical and responsible approach to technology that aims to alleviate the developmental challenges of the planet in a sustainable way [30,87]. This approach—using AI to solve sustainability challenges and using AI in a more sustainable way—will also serve as an enabler of smart city transformation [88,89].

4. Green Sensing, Communications and Computing

Now that we have discussed a number of policy and high-level issues related to green AI, we will define and discuss issues that relate to the development of digital infrastructure for green AI. Our intention is to discuss these infrastructural issues here, together with the high-level issues, and to provide a holistic overview such that different communities working in policy and infrastructure research can understand the cross-disciplinary issues, and collaboratively devise holistic and globally optimum solutions.

Sensing, communications, and computing have never been so interdependent as they are now due to the emergence and convergence of technologies, including the miniaturization of sensors, Internet-of-Things (IoT), data-driven methods, AI-driven optimizations, and cloud, fog and edge computing. The whole ecosystem of smart applications and systems is converging due to the need for these applications to be intrinsically collaborative and distributed.

These smart applications and systems require a certain level of smartness that enhances our ability to engage, sense and act on our environments, analyze them, and make timely, effective and sustainable decisions [90]. The trend is an increase in the number of IoT devices, expected to reach 25 billion by 2030 [91], which in turn increases the requirements for data pre-processing, storage, communications, and processing. AI provides the brain of the smartness, i.e., it undertakes the analyses and the decision-making processes. AI, while requiring significant computational resources (storage, communications and processing), has the capability to improve the efficiency of the whole infrastructural ecosystem via the holistic analysis and optimization of the system.

To aid in the development of green AI, both at the policy and the infrastructure level, we herein introduce and define the concept of "green sensing" as physical and virtual green sensing to enable triple bottom line (social, environmental and economic) sustainability. The definition proposes the development of methods and technologies to sense and measure social, environmental and economic sustainability. Sustainability is affected by challenges such as security, privacy, the safety of people, ethical standards and compliance, and so on, and therefore these are included in our definition of green sensing. These methods and technologies should be green in terms of their efficiency and energy usage.

What are the potential examples of green sensing methods and technologies in the broader sense of the term green sensing, as we have defined it above? A physical sensor to measure the sustainability of urban infrastructure and environmental pollution can be considered a green sensor [92,93]. A virtual sensor, such as that using big data or social media data to detect congestion on the road, can be considered a green sensor for environmental sustainability, in the sense that it detects the environmental pollution that may be caused by a high intensity of pollution in the geographical area where congestion is happening [94].

The same can also be considered a green sensor for social sustainability (or a social sustainability sensor) because it can detect people's anguish, and the potential health-related harms to the people living in or travelling through said geographical area [95]. AI-based virtual sensors can be developed by analyzing various literature, news media, or government regulations in order to understand their economic impacts and sustainability. The possibilities are almost endless. Sensors fit into two broad types: the ones that measure the impact of phenomena directly (e.g., the power or gas/petrol consumption of a community, or real-time or future crowd detection in public spaces) [96,97], and those that measure the impact indirectly (e.g., via social media) [98,99].

The concept of green sensing used here is different from and much broader than the earlier usage of this term, which refers to the methods used to save energy in the sensing process. The earlier use of the term mostly appeared in the context of wireless sensor networks (WSNs) [100]. A range of methods and technologies have been developed under the umbrella of wireless sensor networks to reduce the energy usage of sensors. These techniques have been naturally extended to the IoT paradigm. WSNs and IoTs have been used for many applications, including for environmental monitoring and protection, such as forest fire detection, ambience monitoring, and so on. The main motivation for developing these techniques has been to reduce the energy required by the sensing devices, which are typically wirelessly connected and battery powered.

The techniques to save energy include duty cycling (periodically turning the radio on/off to save energy), wake-up radio (on-demand radio on/off), sensor selection or scheduling (selection or scheduling of a subset of sensors instead of all the sensors), adaptive sampling (adapting the selection of sensors based on the context and application), and more. These green sensing techniques can not only reduce the energy required for sensing, but they also reduce the generated data, reducing the energy needed for data storage or pre-processing. Energy harvesting techniques by all, or a selection of, sensors using renewable energies or electric signals have also been proposed to make the sensing process greener [101].

The data sensed through IoT and other media are usually transferred to a central location, such as a master node or a cloud computing center, for their analysis. An astonishingly large amount of energy is required to transfer data across networks. Naturally, a range of techniques have been developed to reduce data communication energy and improve network efficiency. In addition to reducing data generation through the various green sensing techniques mentioned earlier, various data pruning methods have been developed, such as using data compression to reduce communication and bandwidth requirements.

Probably the most important development in this respect is fog and edge computing-based solutions, which reduce the data transfer and bandwidth requirements of smart applications by processing data at the edge or fog layers, near the sensors and devices, while offering other benefits such as data security and privacy. Several works have investigated the energy efficiency and other benefits of fog- and edge-based solutions [102].

For instance, Janbi et al. [103] developed a framework for the provision of distributed AI as a service (DAIaaS) in future environments. The framework divides "the actual training and inference computations of AI workflow into smaller computations that are executed in parallel according to the level and capacity of resources available with cloud, fog, and edge layers" [103]. They consider "multiple provisioning scenarios for DAIaaS in three case studies comprising nine applications and AI delivery models and 50 distinct sensor and software modules", and report the energy consumption and other benefits of edge- and fog-based AI delivery solutions.

Mohammed et al. [104] proposed the UbiPriSEQ framework, which aims to holistically and adaptively optimize energy efficiency, security, privacy, and quality of service (QoS). They reported an implementation of the proposed framework using deep reinforcement learning (DRL), which allows for devising policies and making decisions related to important parameters, such as transmit power, the specific fog nodes to be selected for offloading data and computation, and so on.

A number of key technological developments are shaping the development of high-speed and low-latency networks, such as fifth-generation networks (5G), which offer a powerful system for ubiquitous environments with advanced sensing and processing capabilities, along with IoT [104]. The requirements of next-generation societies are underpinned by the need to ubiquitously deliver smart services (AI and data-driven) and to increase the numbers of sensors, and these requirements are expected to be met by 6G, the next generation of cellular networks [103–106].

The 6G networks are expected to meet these requirements by use of higher-spectrum and multiple communication technologies [107], ultra-dense heterogeneous networking [106], terrestrial and non-terrestrial communications [108], and the use of AI to optimize service-oriented network operations [109,110]. An important feature of the 6G networks would be their support of ubiquitous AI services. More importantly, energy efficiency is considered the critical requirement of 6G, and this feature is expected to be ten to a hundred times better than that of 5G, achieved using novel antenna designs, zero-energy nodes, and other technologies related to low-rate sensing applications [105,111].

Energy efficiency is a grand challenge in the design of large-scale computing systems, such as supercomputers and computational clouds. For example, the system that is currently ranked number one on the list of the top 500 supercomputers, Fugaku, has over seven million cores and requires 28.3MW of power for its operation. While AI algorithms consume large amounts of power, they can be used to reduce the energy requirements of computations while optimizing performance [112], thus allowing for the concept of green (virtual) sensing and optimizations to be introduced into computing systems.

5. Final Remarks: Policy Directions for Making AI Greener and Cities Smarter

This perspective paper generally contributes to the growing AI literature by underlining the fundamental shortfalls in mainstream AI system conceptualizations and practices, and by advocating the need for a green AI approach to further support smart city transformation and SDGs.

The paper also provides a perspective on the green AI concept. It defines and elaborates on the concept, and discusses why a consolidated effort is needed in the area, including the benefits of a strengthened green AI approach. The elaborations are supported by the literature from diverse disciplines, including computer, environmental and social sciences, and urban studies. The paper also discusses issues that relate to the development of digital infrastructure for green AI. The intention is to discuss these infrastructural issues together with other high-level issues, and to provide a holistic overview such that different communities working in policy and infrastructure research can understand cross-disciplinary issues and collaboratively devise holistic and globally optimum solutions.

Moreover, in order to aid in the development of green AI, both at the policy and infrastructural levels, the paper introduces and defines the concept of "green sensing" as physical and virtual green sensing to enable triple bottom line (social, environmental and economic) sustainability. This paper also highlights the importance of, and advocates the need for, the development of methods and technologies to sense and measure social, environmental and economic sustainability.

This perspective piece makes an invaluable contribution to the emerging field of green AI, as there is no scholarly literature that discusses the policy and infrastructural issues of the given topic in an abstracted way. Our approach here allows readers to gain a holistic understanding of the issues related to green AI via a relatively succinct perspective piece, and presents prospective research and development directions.

We conclude the paper with the following remarks, as it is highly important to have timely, effective and efficient government policy in place for making AI greener and our cities smarter.

Firstly, we underline that the field of AI is growing rapidly; technological advancements are exponential, and applications are disruptive [113,114]. In such a situation, without appropriate government intervention, the business-as-usual scenario will create extended negative risks and consequences for our society and the planet [115]. Unfortunately, these risks and consequences have not yet been fully understood by governments, which means they do not act upon them or take preventative measures [116].

Secondly, as evidenced in the literature, there are colossal policy challenges in the way of making AI green [117]. Perhaps the most critical one is the need for governments to develop legal and ethical frameworks for AI and its use [118]. Expanding on this issue, Dwivedi et al. [65] listed fairness and equity, accountability and legal issues, ethics, misuse protection, transparency and auditing, and digital divides and data deficits as the fundamental public and environmental policy challenges of AI. Another study, by Jobin et al. [119], disclosed "the primary AI ethical principles as follows: transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, freedom and autonomy, trust, sustainability, dignity, and solidarity". These principles are critical to AI projects' ability to deliver the desired outcomes to all.

Thirdly, up until now, no country has passed an AI law yet, and only a small number of countries have attempted to introduce AI ethical frameworks and regulation guidelines—such as the European Union's AI ethics guidelines, intended to inform future regulation, and other examples include AI ethical frameworks in Australia, Germany, Singapore and the UK [120]. The most popular existing practice for most governments seems to be adopting a "wait-and-see" approach to AI ethics and regulations [121]. Furthermore, as stated by Hagendorff [122], in most cases, the existing ethics frameworks fail to serve their purposes, as they lack any reinforcement mechanisms—in other words, there are no consequences if these ethical principles are not followed.

Furthermore, having no regulation at present does not mean that the AI domain will not be regulated in the near future—in this regard, we note the EU's recently released pioneering AI regulation [123]. It is very likely that, as has happened in cases of sharing economy applications, e.g., Uber and AirBnB [124,125]—governments will eventually regulate the AI practice to alleviate its undesired consequences [126]. As stated by Yara et al. [87], "with the development of technology, changes are needed in the legal regulation of AI so that the consequences of its use become useful for the whole society. Market forces with their own resources will not ensure successful development for the whole population. Thus, legal regulation of AI is inevitable."

Lastly, there is a critical role to be played by all stakeholders, e.g., public and private sectors, academia and the public, to make sure that forthcoming AI plans, ethics and regulations also bring efficiency, sustainability and equity perspectives to the technology domain, which will ultimately help in achieving SDGs [127,128]. This renewed green AI approach and capacity will also consolidate the efforts made to transform our cities into smart ones, and support the smart and sustainable development of our cities and communities [129]. In other words, as also indicated by Fisher [130], we need to put our best effort into making AI an efficient, sustainable and equitable technology for establishing smart cities and sustainable futures.

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