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Review

Contributions and Risks of Artificial Intelligence (AI) in Building Smarter Cities: Insights from a Systematic Review of the Literature

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Abstract: Artificial intelligence (AI) is one of the most disruptive technologies of our time. Interest in the use of AI for urban innovation continues to grow. Particularly, the rise of smart cities—urban locations that are enabled by community, technology, and policy to deliver productivity, innovation, livability, wellbeing, sustainability, accessibility, good governance, and good planning—has increased the demand for AI-enabled innovations. There is, nevertheless, no scholarly work that provides a comprehensive review on the topic. This paper generates insights into how AI can contribute to the development of smarter cities. A systematic review of the literature is selected as the methodologic approach. Results are categorized under the main smart city development dimensions, i.e., economy, society, environment, and governance. The findings of the systematic review containing 93 articles disclose that: (a) AI in the context of smart cities is an emerging field of research and practice. (b) The central focus of the literature is on AI technologies, algorithms, and their current and prospective applications. (c) AI applications in the context of smart cities mainly concentrate on business efficiency, data analytics, education, energy, environmental sustainability, health, land use, security, transport, and urban management areas. (d) There is limited scholarly research investigating the risks of wider AI utilization. (e) Upcoming disruptions of AI in cities and societies have not been adequately examined. Current and potential contributions of AI to the development of smarter cities are outlined in this paper to inform scholars of prospective areas for further research.

Keywords: artificial intelligence (AI); AI technologies; AI algorithms; disruptive technology; smart city; smart urban technology; urban informatics; sustainable urban development; climate change

1. Introduction

There exists a strong scientific consensus that anthropogenic climate change is the biggest crisis of our time [1,2]. In a rapidly urbanizing world, climate change and the misuse and mismanagement of land and resources are triggering natural disasters and increasing their intensity [3,4]. Subsequently, cities are becoming frequently subjected to the direct or indirect impacts of natural disasters—for example, the 2019 Amazon Rainforest fires [5] and the 2020 Australian bushfires [6]. There have been numerous top-down (e.g., the Paris Agreement, Intergovernmental Panel on Climate Change, UN's Sustainable Development Goals, UN Climate Change Conferences) and bottom-up (e.g., school strikes, extinction rebellion protests, climate emergency declarations) attempts to raise awareness and develop policy actions to address the climate emergency [7,8].

These efforts provided some hope, despite the political and policy quagmires in many countries. Nevertheless, there has been no significant climate action undertaken to address the crisis. Instead, in recent years, with the advancement of the current digital revolution, a large portion of policymakers, practitioners, and scholars have increased their faith in smart urban technologies to mark a major turning point in the history of humankind [9]. This technocentric view—in solving urban and environmental problems with the aid of technology—has increased the popularity of the 'smart cities' notion [10]. These cities—also referred to as 'geographies of disruption' [11]—harness digital technologies to offer new business opportunities, shape the urban fabric, improve the quality and performance, and overcome many of the challenges confronted by urban areas [12].

The prospects of smart urban technologies range from expanding infrastructure capacity to generating new services, from reducing emissions to engaging the public, from minimizing human errors to improved decision-making, and from supporting sustainable development to improving performances of commercial enterprises and cities [13,14]. The most popular technologies in the context of smart cities include but are not limited to internet-of-things (IoT), autonomous vehicles (AV), bigdata, 5G, robotics, blockchain, cloud computing, 3D printing, virtual reality (VR), digital twins, and artificial intelligence (AI) [15–17]. While all these technologies are critical in transforming our cities into smarter ones, AI combined with these technologies has significant potential to address the urbanization challenges of our time [18]. Furthermore, AI is certainly seen as the most disruptive technology among them [19,20].

The prospective benefits of AI for cities continue to be discussed in the literature in the context of smart cities—that are enabled by community, technology, and policy to deliver productivity, innovation, livability, wellbeing, sustainability, accessibility, as well as good governance and planning [15,21,22]. Despite the growing number of articles on the topic, there is no scholarly work that provides a comprehensive review of the growing literature. This paper organizes the literature to examine how AI can contribute to the development of smarter cities. As the methodologic approach, the study adopts a systematic literature review on the topic of 'AI and the smart city'.

2. Conceptual and Application Background

In broad terms, AI is defined as "machines or computers that mimic cognitive functions that humans associate with the human mind, such as learning and problem solving" [23]. In other words, AI, where machines mimic human cognitive functions, can make decisions, think, learn and improve themselves. It was first introduced in 1956 at Dartmouth College, but development was slow until recently due to immature computational technologies. In recent times, advances in hardware, software, and networking technologies have enabled us to design, develop, and deploy AI systems at scale. The application areas of AI ranges from banking and finance to marketing and gaming, and from agriculture and healthcare to AVs and space exploration—and many more areas [24].

AI-driven computational techniques are diverse and range from rule-based systems to deep learning systems. A popular AI knowledge map was created by Corea [25]. His conceptualization brings together the AI paradigms and the AI problem domains (Figure 1). The X-axis categories various computational paradigms and the Y-axis outlines problem domains. Various technologies are then mapped to illustrate their potential value. For example, rule-based systems (e.g., expert systems, robotic process automation) that are logic-driven knowledge engines, which are common in urban systems, are often used to capture and automate structured workflows.

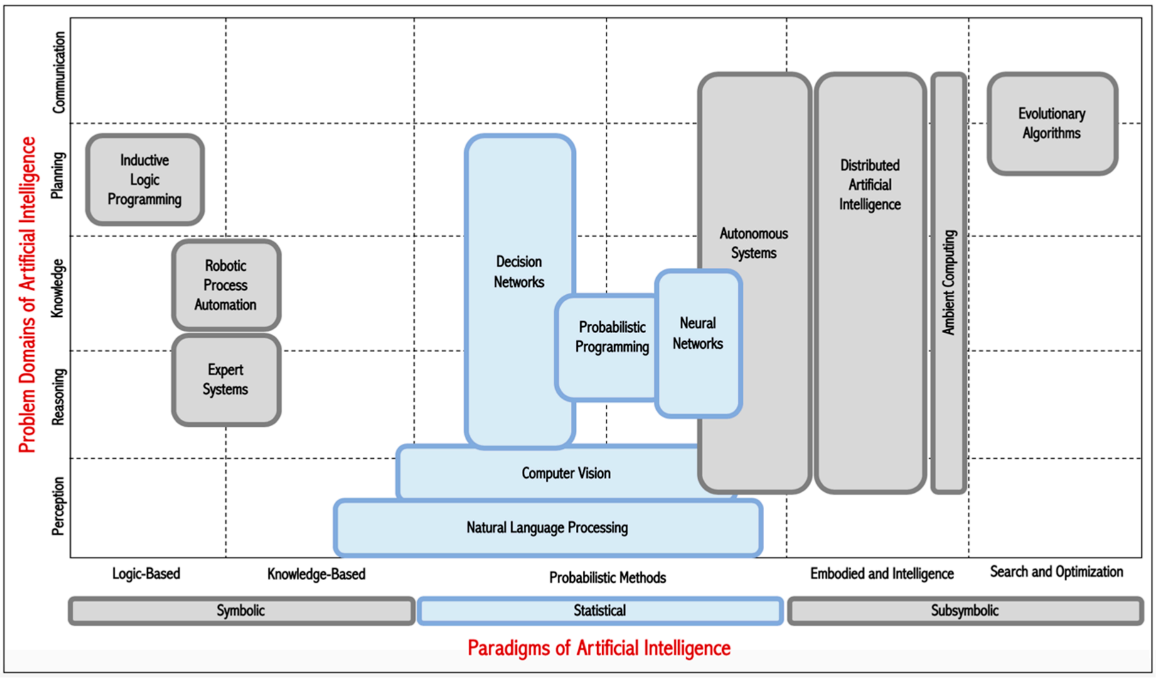

Figure 1. AI knowledge map, derived from [25].

Today, AI applications are being deployed in all facets of cities [26,27]. We can classify these applications based on their underlying AI technologies along with other relevant smart technologies as shown in Figure 1.

AI applications are used to improve and innovate the delivery of public services [28]. Various cities have begun 'robotic process automation' (RPA) projects. These projects are focused on automating tasks that are currently conducted by public workers that are mundane, repetitive, and costly. Thus, freeing up valuable resources to be better deployed. Cities are using RPA to process online applications for items such as permits. RPA follows structured rules to reach an outcome [29].

The interest in autonomous vehicles (AV) is palpable. AVs open opportunities for cities to modernize their public transport infrastructure [30]. Autonomous buses are expected to start carrying fare-paying customers in Scotland by mid-2020 after successful trials across a 14-mile route on the Forth Road Bridge between Fife and Edinburgh. All Nippon Airways (ANA) has commenced trials of autonomous buses with minimal human oversight at Haneda International Airport [31]. Depending on the success of these trials, ANA plans do a full-scale deployment by the end of 2020. In recent times, we have also seen AVs complete successful tests in more complex urban environments including London and Paris [32].

The interest in autonomous systems is not limited to RPA or AVs. Smart cities are exploring how to take advantage of advances in robotics [33]. The City of Houston will be beginning trails of robot police shortly at various transit centers to curb petty crime and free up law enforcement resources [34]. Robots are also being tested to augment law enforcement personnel and lower incidents of conflict between them and the public. In the US where, in recent times, several routine traffic stops have led to confrontations, robots are being tested in mediating encounters between police officers and drivers [35].

Engagement platforms between public agencies and various stakeholders of the city are also being transformed through a range of AI applications. Chatbots are the most popular set of AI applications in this regard. Rammas, a chatbot, was deployed by the Dubai Electricity and Water Authority (DEWA) in January 2017 [36]. DEWA can respond to queries from residents in Arabic and English, and promotes greater knowledge awareness on utility matters. In its first year of operations, Rammas responded to roughly 700,000 queries, which led to an 80% drop in in-person visits.

AI systems ingest vast amounts of data, apply learning algorithms, and learn patterns from the data to enable predicting outcomes [37]. Today, cities are deploying machine learning systems to exploit data across their ecosystem from sensors on public infrastructure, to machine readable cards that provide access to city services (e.g., public transport), to images and videos that capture movements around the city, and even devices that capture auditory, olfactory, and tactile data [38,39]. Urban infrastructures, such as traffic lights, are becoming connected. Traffic lights are connected to road sensors to reduce wait time at signals based on the traffic flow. Scotland's Glasgow city has installed networks of sensors that connect to streetlights and traffic lights to help monitor traffic flow and increase connectivity, aggregately reducing travel time for drivers. Further, the traffic data also feeds into maps in real-time to help drivers, cyclists, and pedestrians make decisions to plan their commutes [40].

The Las Vegas Health Department, in partnership with the University of Rochester trialed the nEmesis app which utilized machine learning to collect and examine tweets, the purpose of which was to select restaurants which were suitable for inspection [41]. Following controlled experiments, the nEmesis app was found to be 64% better at identifying restaurants with food safety issues than established processes involving random inspections. It also had success at identifying restaurants that were unlicensed and had infectious staff. Overall, the app was very effective at helping the Las Vegas Health Department address issues with their restaurant inspection process without the need for additional resources [41]. The harm assessment risk tool (HART) was developed by UK's Durham Constabulary to detect patterns of recidivism among criminals [42]. The tool was trained on crime data from 2008–2012, including information about suspects' gender and zip code. The tool was used to predict the recidivism rate in 2013. It successfully predicted 98% of low-risk offenders and 88% of high-risk offenders.

In 2017, the Seattle Police Department launched a data analytics platform to transition towards improved oversight, data-driven decisions, and community engagement [43]. This platform helps the department to manage, govern, and support insightful policing. The system is designed to help the department's leadership team to track trends related to operations. It integrates 17 internally tracked metrics and develops visualizations for department heads. The system tracks several measures such as use-of-force incidents, number of arrests, self-initiated trips, response to calls, number of stops, and civilian complaints. The department can use this detailed information on each police officer to take appropriate measures (e.g., counselling). Since 2012, the police department in San Diego has collected over 65,000 face scans, in an attempt to match them to a directory of over 1 million images collected as part of the San Diego County Sheriff's Tactical Identification System (TACIDS) [44]. More recently, London Metropolitan Police has announced plans to use facial recognition technology to aid police in identifying suspects.

While the housing and urban development space today is data rich, much of the data is often left unanalyzed, thereby resulting in an inability to keep policies and enforcement standards current. Researchers from Georgia Institute of Technology, Emory University, and University of California, Irvine collaborated with the Atlanta Fire Rescue Department (AFRD) to develop an algorithm which was able to predict fire risk in buildings [45]. Using data from 2010–2014, the algorithm included over 50 variables—including property location, building size, structure, age, and history of fire incidents—to predict fire risk. The algorithm classified fire risk ratings for 5000 buildings and found another 19,397 buildings requiring inspection. Furthermore, the algorithm was able to predict 73% of fire incidents which occurred within the study area [45].

AI-enabled computational tools also help in protecting cyber-infrastructure that is the core fabric of smart cities [46]. Four US cities, namely Pensacola, New Orleans, Galt, and St Lucie, were all victims of different cyberattacks throughout December that rendered telephone and email systems, law enforcement systems, waste, energy, and payment systems inoperable. Often, these attacks demand a ransom, and councils find themselves either paying the attackers or employing external cybersecurity and consulting firms to mitigate and repair the situation. In Lake City, Florida, council reluctantly paid a $460,000 'ransom' to attackers after all their council systems were shut down [47]. Researchers from MIT developed an AI platform called AI2 that outperforms existing systems in predicting cyber-attacks [48]. AI2 detects 85% of cyberattacks, performing about 300% better than previous systems. The system is also able to reduce the instance of false-positive readings to one-fifth of previous outcomes. This high detection rate is enabled through supervised and unsupervised machine learning.

While we have treated each AI application in isolation, it is common to have them bundled and integrated. Researchers from Carnegie Mellon University collaborated with the City of Pittsburgh to develop a Scalable Urban Traffic Control (SURTRAC), which was able to simultaneously monitor and control the flow of traffic [49]. The system has been deployed in the East Liberty neighborhood since 2012 and covers nine intersections. On average, 29,940 vehicles pass through this area daily. SURTRAC is a schedule-driven system designed to manage multiple competing traffic flows shifts. SUTRAC is a multi-agent decentralized system, where an agent system runs each intersection. Each agent system controls traffic signals for their intersection and monitors traffic flow by dynamically coordinating with other agents in real-time. The deployment of SURTRAC resulted in a 34% increase in vehicle speed, and a reduction of 25% in travel time, 40% in waiting time, 31% in traffic stops, and 21% in emissions.

While AI systems have significant potential, their deployments are never straightforward. In Detroit, a $9 million initiative 'Neighborhood Real-Time Intelligence Program' implemented facial recognition software and video surveillance cameras at 500 different Detroit intersections. This initiative built on the previous 'Project Green Light' Initiative, which installed 500 cameras outside of businesses capable of recording and reporting real time video footage to the police. The software boasts an ability to match faces with 50 million driver's license photographs in the Michigan police database. Nevertheless, recent research has shown that current facial recognition software more often misidentifies black faces than white faces [50]. Whilst intended to increase public safety, there is widespread public criticism directed towards this technology, as residents feel their privacy is compromised and knowledge of the racial biases continues to increase.

Fake news in its purest form refers to completely made up information, nonetheless, such information is often hard to identify as it can resemble credible journalism and attract maximum attention, spreading like wildfire through various social media channels [51]. A man was caught after he carried an assault rifle and fired shots at a pizza parlor in Northwest Washington Upon arrest, the man informed the police that he was investigating a conspiracy theory which claimed that the pizza parlor—Comet Ping Pong—was the headquarters of a pedophilia ring [52]. This incident caused panic among people in the neighborhood, resulting in the lockdown of several businesses.

In Arizona, the hotbed for testing of AVs by major technology providers, we have seen incidents of residents throwing rocks at these vehicles [53]. There, AVs are seen as a threat to jobs, livelihood, and are a source of frustration. As noted by Selby & Desouza [54], "If theory and practice advance over the next few years without paying attention to fragility, then cities will continue to be vulnerable to manageable threats. As the trends of urbanization continue, it is even more imperative to attend to fractures of social compacts. Cities will continue to grow, and their complexity will only increase. This complexity will continue to mask fragility in the city and could result in the breakdown in one of our society's most valuable artifacts, developed cities, representing a potential loss of life and economic prosperity". AI technologies, for all their good, do make cities more fragile [55] as they put pressures on local governments to maintain existing, and strengthen, social compacts in the face of job losses, automation, shifts in public finances, and so on.

In May 2016, a Tesla Model S car collided with a tractor-trailer in Williston, Florida. The accident occurred on the highway when the car, on autopilot mode, collided with the truck while crossing an uncontrolled intersection. The Tesla driver sustained fatal injuries, raising several questions about the autopilot functionality. However, the National Highway Traffic Safety Administration's (NHTSA) final investigation report concluded that the accident was caused by the driver's inattention [56]. Since the accident, Tesla has implemented several features to keep drivers engaged while their car is in autopilot mode.

Chrysler recalled about 1.4 million cars and trucks, because these vehicles could be hacked remotely over the Internet [57]. These vehicles used UConnect features to connect with Sprint networks for navigation. Hackers could access these cars' navigation systems to control air conditioners, cut off brakes, and shut down engines, and so on. Software installed in vehicles need to be constantly upgraded to protect against hacks and security breaches [58].

Economically, local governments may lose revenue streams because of AVs due to a decrease in speeding tickets, towing fees, and driving under influence charges [59]. Cities in Arizona such as Phoenix and Mesa collected about $10.8 million and $4.2 million from drivers for traffic violations [60]. On an average, cities in California generated $40 million in towing violations annually [15].

The conceptual and application background of AI as presented above underlines the importance of further investigations into how we can best integrate AI systems in addressing critical urban issues. Particularly the challenges we face—e.g., climate emergency—calls for smarter systems in place. This is also highly critical to increase the smartness of our cities. A recent study that evaluated the smartness levels of 180 Australian local government areas argues for the importance of better integration of urban technologies, including AI, into local service delivery and governance [14].

3. Materials and Method

We undertook a systematic review of the literature to answer the following research question: How can AI contribute to the development of smarter cities? We adopted a three-phase methodologic approach (Figure 2) following the study steps of Yigitcanlar et al. [61].

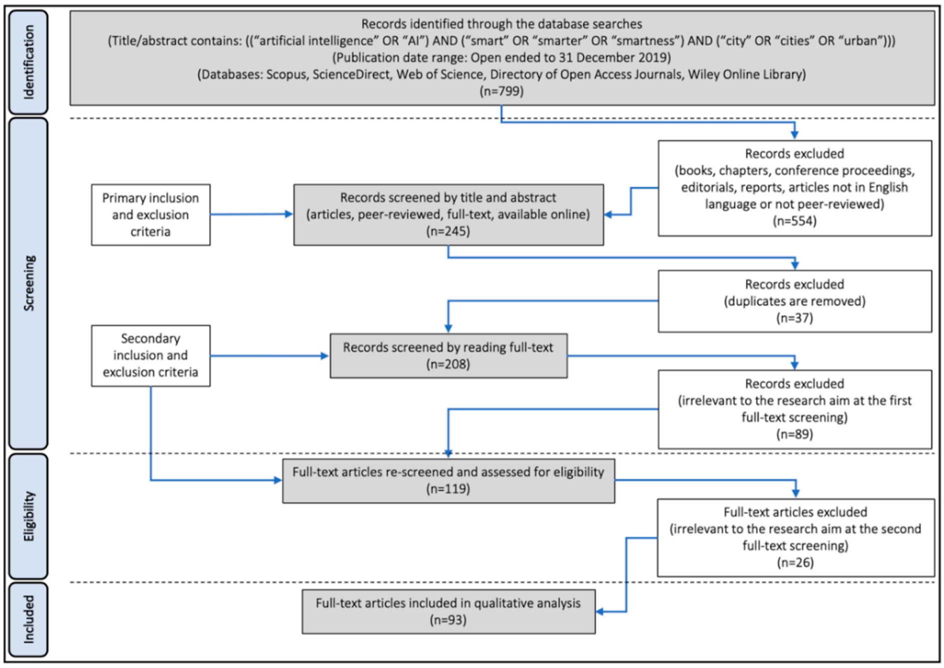

Figure 2. Literature selection procedure.

The first phase is planning, which involves developing the research aim, research question, a list of keywords, and criteria for the inclusion and exclusion of articles. The research aim was framed to generate insights into forming a greater understanding on how AI can contribute to the development of smarter cities. The inclusion criteria were intended to be peer-reviewed journal articles, that were available online, in English, and had relevance with respect to the research aim. A university's library search engine, which gives access to 393 different databases including: Directory of Open Access

Journals, Science Direct, Scopus, TRID, Web of Science, and Wiley Online Library, was used to complete an online search. The search was carried out towards the end of December 2019 using the query string of ((“artificial intelligence” OR “AI”) AND (“smart” OR “smarter” OR “smartness”) AND (“city” OR “cities” OR “urban”)) to search the titles and abstracts of available articles. The publication date was left open. From this search it was determined that the one of the earliest studies on AI and the city was from Schalkoff [23]. The abstracts were then read, and if the article was considered to be relevant to the research aim, the full-text was reviewed to decide whether it was suitable to include in final analysis.

The second phase involved carrying out the review of relevant articles. The initial search resulted in a total of 799 records. These records were then screened and reduced to 245 by applying the inclusion criteria—i.e. journal articles that were peer-reviewed, and available online. The articles were then ‘eye-balled’ to ensure they were consistent with the keyword search, the abstracts assessed against the research aim, and duplicates removed. The total number of articles was reduced to 208. The full-text of the selected articles were read to determine the relevance with respect to the aim of the study and the results were narrowed down to 119 articles. After another round of full-text screening, the number of articles was reduced to 93. Finally, these 93 articles were reviewed, categorized, and analyzed. The criteria for formation of the themes is presented in Table 1. For the categorization, the main smart city development dimensions—i.e., economy, society, environment, and governance—were selected. Figure 3 below presents these dimensions in the context of smart cities.

Table 1. Selection criteria for formulating categories.

Selection Criteria
1. Determine the literature relevant to the research aim by using the eye-balling technique;
2. Identify the suitable literature pieces focusing on AI and smart cities after reading the full-text;
3. Group the identified AI technology, algorithm and application areas with similarities into broad categories;
4. Narrow down the selected categories and review the reliability of these against other published literature;
5. Review the selected literature again and update the shortlisted categories if necessary;
6. Confirm and finalize the categories selected for the classification of literature;
7. Catalog the literature selected for the review under the selected categories.

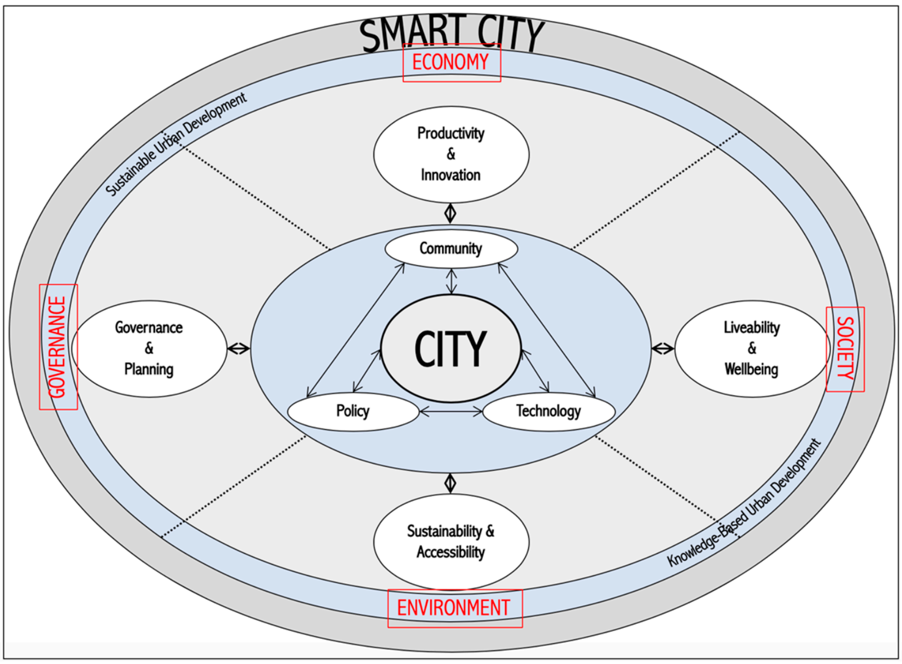

Figure 3. Smart city conceptual framework highlighting key domains, derived from [62].

The third and final phase is reporting and dissemination. This phase involved critically documenting and presenting the results from the 93 articles analyzed. A discussion of the perceived benefits and concerns associated with AI implementation were outlined.

4. Results

4.1. General Observations

The first step in the analysis of the selected 93 articles was to classify them by date of publication. This process revealed interest in AI technology had grown exponentially in recent times. Almost half of the reviewed articles were published in 2019 (n = 46; 49%), one-fifth in 2018 (n = 18; 20%), and nearly one-tenth in 2017 (n = 8; 9%). Slightly less than a quarter of all articles were published before 2016 (n = 21; 23%). The earliest article included in the literature review was published in 1999. Despite the fact that articles on AI and the city dated back to 1990, the earliest one that met our selection criteria was [63]. These figures reflect the results of other review studies and are representative of the increased interest in how AI systems interact and impact the development of smart cities [64].

Leading authors are affiliated with institutions in Europe (n = 28), East Asia (n = 24) and North America (n = 21). Nonetheless, the Oceania context, particularly in Australia, is often referenced among the best applications of AI in practice [65,66]. Regarding the academic journals, the articles published in IEEE Access appear most often (n = 8), followed by Sensors (n = 5), and then three articles in both Artificial Intelligence in Medicine (n = 3) and Procedia Computer Science (n = 3).

Articles were categorized under four groups. These groups were based on the main smart city domains of: (a) Economy; (b) Society; (c) Environment; (d) Government. More than one-sixth of them (n = 17) were in the economy domain, slightly more than a quarter (n = 24) in the society domain, over one-third (n = 33) in the environment domain, and slightly less than quarter of them (n = 19) were in the governance domain.

With reference to the 'AI Knowledge Map' (Figure 1), the majority of articles discusses AI applications or techniques that fit within the machine learning paradigm (n = 71), followed by probabilistic methods (n = 25), knowledge-based (n = 21), search and optimization (n = 21), logic-based (n = 18), and embodied intelligence (n = 15). Regarding AI applications, the most commonly mentioned in the selected literature are neural networks (n = 55), evolutionary algorithms (n = 21), distributed artificial intelligence (n = 15), computer vision (n = 13), and decision networks (n = 9). The most common AI paradigms and applications identified in the literature are outlined in Table 2. A complete list of all articles and the identified AI paradigms, applications, techniques, and supporting technology are shown in Appendix A. Please note, there is some crossover with the number of AI paradigms and applications identified in the literature as many articles discuss multiple, or hybrid AI systems.

We acknowledge that there is a potential risk in bias resulting from our strategy for selecting literature to be included in the review. Our review focused on journals only, whereas cutting edge works in engineering, design, and technology field are often published in conference papers. Nonetheless, in order to complement the reviewed 93 journal articles, the paper also cited or quoted 112 relevant literature pieces on the 'AI and smart cities' topic.

4.2. AI in the Economy Dimension of Smart Cities

Papers categorized under the economy dimensions of smart cities are those that provide insights into 'how AI can contribute to and enhance the productivity and innovation of smart cities' [33]. Research in this area focused predominately on technological innovation, economy and management areas, and the contribution of AI can be summarized as: (a) Enhancing productivity and innovation by automating data management and analysis; (b) Reducing costs and increasing resources through pattern recognition; (c) Supporting decision-making by analyzing large volumes of data from multiple sources, and; (d) Drawing conclusions based on logic, reason and intuition. Appendix A lists the analysis highlights of the reviewed literature.

Table 2. The common AI paradigms and applications identified in the literature.

Category	Element	Reference
AI paradigms	Machine learning	[26]; [63]; [67–70]; [71–135]
	Probabilistic methods	[70]; [73–75]; [77]; [80–82]; [87]; [90]; [93,94]; [96–101]; [112–114]; [134]; [136–138]
	Knowledge-based	[26]; [63]; [67–71]; [73]; [77,78]; [82]; [92]; [98]; [100]; [112]; [136]; [139–143]
	Search and optimization	[26]; [67–69]; [77]; [79,80]; [82]; [86]; [92]; [98]; [101]; [106]; [112]; [116]; [128]; [130]; [134]; [144–146]
	Logic-based	[63]; [67,68]; [69]; [71]; [73]; [77,78]; [82]; [92]; [98]; [100]; [112]; [136]; [140–143]
	Embodied intelligence	[26]; [70]; [73]; [75,76]; [80]; [82]; [98]; [104]; [116]; [128]; [134]; [137]; [147]
AI applications	Neural networks	[26]; [63]; [67–70]; [71]; [73]; [75]; [77–85]; [87]; [89,90]; [92]; [95]; [97–103]; [105–107]; [109–112]; [116–126]; [128–134]
	Evolutionary algorithms	[26]; [67–69]; [77]; [79,80]; [82]; [86]; [92]; [98]; [101]; [106]; [112]; [116]; [128]; [130]; [134]; [144–146]
	Expert systems	[26]; [63]; [67–70]; [71]; [73]; [77,78]; [82]; [92]; [98]; [100]; [112]; [136]; [140–143]
	Distributed artificial intelligence	[26]; [70]; [73]; [75,76]; [80]; [82]; [92]; [98]; [116]; [128]; [134]; [137]; [147,148]
	Computer vision	[73–75]; [87]; [93,94]; [96]; [99]; [101]; [113,114]; [118]; [138]
	Decision networks	[70]; [77]; [80]; [82]; [90]; [98]; [112]; [134]; [136]

AI is a useful tool to quickly and accurately manage and analyze large volumes of data to support business decisions [103,112]. This is particularly relevant in combination with IoT—a system enabled by the internet, which allows communication between a large network of devices without the need for human intervention [77,106,110]. Together with technologies such as blockchain, cloud storage, and fog computing—which help facilitate the recording, distribution, storage, and decentralized processing of data [128,149]—, AI could improve productivity by automating the data management process and removing the need for intermediaries, and hence increasing profitability [126]. Furthermore, AI can improve the stability and effectiveness of IoT contributing to improved network communication. In return, this would help to improve knowledge sharing, and foster innovation and entrepreneurship [106,127,128].

AI can be used to recognize patterns in datasets, helping to optimize the data management process, improve the overall productivity of the data management system [111,149], and identify cyber-attacks [107], coding errors, and other inefficiencies [103]. Deep learning has already had success recognizing patterns from a wide range of data sources including images, audio, video, and other sensors [104]. The application of AI has the potential to remove the need for humans to complete many repetitive business tasks—particularly those relying on observation—,potentially reducing costs and freeing up resources for more productive or innovative fields [112,130].

In analyzing the large amounts of data collected by the sensors, devices, and other sources in a smart city, AI has the potential to accelerate the decision-making process by automating complex statistical analyses [111,130,150]. This is particularly relevant with regards to the application of deep learning technology to the process of data fusion—i.e. the processes of taking data from a variety of sources, combining it, and improving its quality and usefulness by producing sophisticated statistical models [126]. AI has the capability to automate this process and conduct statistical analyses that are much larger and more complex than could be completed with human intervention. This information can then be used to reduce economic uncertainty and assist business decisions [77,103,107], and/or create marketplaces that are more responsive to user needs and desires [130].

The ability of AI to complete complex statistical analysis can also be used to automate decision-making [128,130,150]. The ability to learn, can ensure that AI systems are responsive to uncertainty, particularly when working with and around humans [94,119]. This can reduce the possibilities of accidents, errors, and improve the operational efficiency of business and industries [119]. Smart control systems can monitor traffic, collect and analyze data and in combination with connected-AVs there is potential to make real-time decisions which enhance the efficiency of transport operations—including freight and supply chain logistics [104,130]. AI systems can be developed with human-like abilities, such as creativity, design, intuition, inventiveness, trust, ethics, and values to perceive, understand, and make informed, reason-based decisions that would benefit companies [76,94].

4.3. AI in the Society Dimension of Smart Cities

Papers in this category provide insights into 'how AI can contribute to and improve the livability and wellbeing of citizens in smart cities' [33]. Research in this area focused predominately on the health and education sectors, and the contributions of AI can be summarized as: (a) Improving health monitoring; (b) Enhancing health diagnosis outcomes, and; (c) Providing autonomous tutoring systems that are highly individualized and adaptive to needs and external changes. Appendix A lists the analysis highlights of the reviewed literature.

AI systems, in combination with sensors, cameras and other data collection devices, have been developed to monitor the health and wellbeing of individuals [70,87]. Machine learning techniques can be used to improve the cost and efficiency of fall detection devices [99], and detect changes in sleep, mood, heartbeat, respiration, and other vital signs [118,129]. Wearable devices, or 'smart textiles, enabled by AI, can detect changes in the human body and report findings to health care providers [129]. In intensive care settings, monitoring devices equipped with AI can be used to adjust the settings on bedside devices reducing total healthcare costs and improving patient outcomes [67]. In rural settings, the ability to monitor patients remotely could contribute to reduced inequities and improve access to healthcare [89]. This is a particularly critical issue in countries like Australia, where in some remote areas the nearest health service provider or hospital could be located 1,000 km or further [151]. Additionally, the smart tracking of health symptoms could improve communication between patients and health care professionals [142].

In addition to health monitoring, AI systems can greatly improve health diagnosis by providing an effective repository of medical knowledge and the ability to access, analyze, and apply complex medical data more efficiently [68,139]. Assisting health care workers with tasks involving the collection and recording of data and knowledge could increase the amount of resources available for patient care [68,139], improve the quality of life for patients [120], and expand the professional learning capabilities of professionals [122]. Similarly, the improved analytics and reasoning capabilities of AI would provide a decision-support mechanism with the potential to reduce chances of misdiagnosis [137], facilitate greater communication and collaboration between health care professionals [70], and assist with the development of more personalized medical treatments [91,137].

With regards to the education sector, intelligent tutoring systems that mimic the one-on-one interaction between tutor and student can provide highly individualized teaching programs for students [140]. Furthermore, these systems can develop multiple paths to answer any given question and provide highly detailed feedback [140]. Advances in AI technology can increase the effectiveness of these, and similar systems by automatically collecting information from the web, ensuring the most up-to-date content, and using machine learning to increase the adaptability to individualized learner requirements [81,146]. There is potential to create systems that are far more effective than one-on-one tutoring [143], with improved communication between student and teacher, and superior assessment methods [85]. This is especially promising with regards to identifying and adapting syllabus to the individual strengths and needs of students with learning disabilities or other special learning requirements [71].

Increased adaptability is important as rapid technological changes are likely to result in an unstable job market [135,143]. AI could potentially bring new skill requirements across multiple sectors and the education sector needs to be at the cutting edge of these changes to ensure students are prepared for future job markets [152]. For example, even in the education sector itself, AI will replace many of the time-consuming tasks, changing teacher roles to one based on student support and the management of AI systems [88,135,153]. Managing the education needs of residents is therefore important to ensure they are able to take advantages of the potential benefits of AI including improved working conditions, better work-life balance, and improved quality of life [135].

Lastly, AI has been used for the modelling of the spread of the recent COVID-19 epidemic. The predictions seem to be showing reliable results as the modelling predicts COVID-19 infections with an accuracy of 96%, and deaths with an accuracy of 99%, up to one week into the future. This information would help governments implement effective contingency plans, and prevent the virus's spread and turn into a global pandemic [154]. Similarly, Lin et al. [155] utilize blockchain with AI to efficiently manage water use under the changing climate conditions, and contribute to climate change adaptation efforts.

4.4. AI in the Environment Dimension of Smart Cities

These papers provide insights into 'how AI could contribute to sustainable urban development and improved accessibility in smart cities' [33]. Research in this area focused predominately on the transport, energy, land use, and environment sectors/areas, and the contribution of AI can be summarized as: (a) Monitoring changes in the environment; (b) Using smart energy systems to optimize energy consumption and production; (c) Planning, development, and use of households to reduce energy consumption, and; (d) Operationalizing smart transport systems. Appendix A lists the analysis highlights of the reviewed literature.

When faced with complex environmental issues and large quantities of data, AI systems have the potential to make knowledge-based decisions that balance the environmental outcomes of the city against the social and economic wellbeing of its residents [63,136]. AI systems can be used to monitor changes in the environment including, noise, temperature, humidity, emissions [90], water pollutants [133], fish stock, and other environmental indicators [136]. AI systems can respond to these changes, and quickly implement solutions for dealing with any issues [156]. Furthermore, improved data quality from AI systems can contribute to more robust and accurate environmental modelling systems [69,124].

AI has also been identified as a means of creating more energy efficient cities [156]. Smart grid systems, integrated with AI technology, can be used to control power systems and optimize energy consumption [78,79]. Including the planning and management of electric vehicle charging [145], public lighting [75], and data [121]. AI can also assist with the distribution of renewable electricity generated from multiple, often non-traditional sources—including body heat [125]—, the identification of inefficiencies, and future forecasting [134,157]. By optimizing the management of resources, monitoring energy consumption, and better planning for future requirements, cities will be able to use resources more efficiently and better achieve renewable energy goals [80,86].

Smarter homes can be developed with AI systems that monitor changes in the environment, adapt to user requirements, and improve energy efficiency [73,92,116]. AI systems could be used to predict future household energy requirements which can help identify inefficiencies, faults, and control future energy use [81]. In addition, AI can contribute to reduced energy consumption in the construction process [102], and improved environmental outcomes in the design [146] and planning process [26].

With regards to sustainable transportation, the goal of AI in the context of smart cities is to calculate the most efficient means of moving people and goods between places, reducing the number of vehicle kilometers traveled (VKT). This in turn leads to a reduction in energy consumption which in turn leads to lower air and noise pollution, congestion, and other externalities such as the requirements for transportation and parking infrastructure [98,156]. AI can be used for transport optimization by analyzing real-time measurements—such as traffic signal control—to adjust routes [74,97], balance user demands [96], and make parking more efficient [104,113]. Particularly in AVs, these changes can result in substantial reductions in travel time and energy savings [108]. From a transport planning perspective AI can also be used to differentiate spatial structures in aerial images [113] and collect masses of data for the development of more accurate, and responsive models which can be used to develop a more environmentally efficient transportation system [117].

Despite no studies in the reviewed literature directly focus on how AI can tackle climate change, we are aware of some relevant research. For instance, in their paper entitled 'tackling climate change with machine learning', Rolnick et al. [158] offer areas where machine learning can be deployed. These areas include better climate predictions and modeling, energy production, CO_2 removal, education, solar geoengineering, and finance. Within these areas, the possibilities include more energy-efficient buildings, creating new low-carbon materials, better monitoring of deforestation, and greener transportation. They state that "although AI is not a silver bullet, it brings new insights into the problem". Another study, by O'Gorman & Dwyer [159], demonstrates the use of machine learning to parameterize moist convection and climate change, and extreme event modelling. Likewise, Dayal et al. [160] model Queensland (Australia) droughts based on AI and neural network algorithms for decision-makers and local inhabitants to take precautions.

4.5. AI in the Governance Dimension of Smart Cities

How AI can contribute to establishing good governance and planning in smart cities is the focus of this set of papers [33]. Research in this area focused predominately on the security, governance and decision-making areas, and the contributions of AI can be summarized as: (a) Enhancing the operability of surveillance systems; (b) Improving cyber security; (c) Aiding the disaster management planning and operations, and; (d) Assisting citizens with new technology to support citizen scientist and contribute to the urban decision-making process. Appendix A lists the analysis highlights of the reviewed literature.

Advanced AI surveillance technologies, enabled by motion detection, predictive analytics, drones, and other autonomous devices, can be used to monitor urban areas, recognize threats, such as crime [72,93,100,148], fraud [109], accidents, and fire [101,123,160]. On a broader scale, AI can be used to monitor communication networks and recognize potential terrorist threats, trafficking, crime syndicates, and other illegal behavior [100]. Once targets are identified, intelligent surveillance systems can evaluate and track targets [93], and collect forensic evidence—such as video recording [138]. AI can also be used to better predict future crime incidents and ensure the optimal allocation of crime law enforcement [144].

Cyber threats also pose significant risks to smart cities both in terms data privacy and the protection of connected infrastructure [83,161,162]. AI can be used to identify irregular behavior, determine what is a threat and implement mitigation measures at speeds beyond that of human ability [83,100]. This together with encryption technologies such as blockchain [100], and a focus on data security at all levels of design [131], can alleviate individual concerns regarding data security and contribute to increased transparency and trust regarding online systems [83,141]. This would allow increased avenues for citizen engagement in policy decisions and citizen scientist engagement with policy development via crowdsourcing [163], along with other online services such as electronic voting [141] and smart contracts [115].

Given the ability of AI to analyze large amounts of data, scenarios to deal with potential threats could be constructed simultaneous to the detection of threats [161]. This would give decision-makers and other authorities more time to respond to threats such as natural disasters [132], house fires [123], or other incidents. Furthermore, AI can be used to assess the extent of damage caused by these events helping authorities better respond to, and mitigate any damage caused [101,132].

Finally, AI systems can be used to both assist and analyze acceptance of new systems—particularly those associated with new technologies [109,163]. Online 'chatbots' can help residents navigate new websites and online platforms [109], with training and tips customized based on individualized needs and interests [164]. Furthermore, AI use reasoning and intuition to assist decision-makers understand the reasons behind citizen acceptance, or non-acceptance, of new technology [165]. Where new approaches are required, AI can develop innovative solutions [95] and address future challenges [84].

5. Discussion

This review study investigated the impact of the two very powerful and highly popular phenomena of our time, i.e., AI and smart cities. On the one hand, the smart city notion is seen as a potential blueprint for the development of future cities to provide improved productivity, innovation, livability, wellbeing, sustainability, accessibility, governance, and planning [166,167]. Nevertheless, we still do not have the technical capabilities to develop these technologically advanced futuristic cities [168]. On the other hand, AI provides a hope for overcoming the limits of human capabilities, in the computational sense [169]. Hence, in theory, a happy marriage of AI and the smart cities concept would bring us closer to producing smarter cities [22].

In this paper, we attempted to generate insights into forming a better understanding on how AI can contribute to the development of smarter cities by undertaking a systematic review of the literature. Appendix A lists the analysis highlights of the reviewed literature. The results of the review disclosed the following main points, and some of the critical issues are discussed further:

1. AI has an evident potential to provide a positive change in our cities, societies and businesses by promoting a more efficient, effective and sustainable transition/transformation;
2. AI, with its technology, algorithms, and learning capabilities, can be a useful vehicle in automating the problem solving and decision-making processes; that in return could reform urban landscapes, and support the development of smarter cities;

3. AI in the context of smart cities is an emerging field of research and practice. Hence, further research is needed to consolidate the knowledge in the field;
4. The central focus of the literature is on AI technologies, algorithms, and their current and prospective applications;
5. AI applications in the context of smart cities mainly concentrate on business efficiency, data analytics, education, energy, environmental sustainability, health, land use, security, transport, and urban management areas, and;
6. Upcoming disruptions of AI on cities and societies have not been adequately investigated in the literature; thus, further investigations are needed on that issue.

The results of the review revealed that AI-inspired computational systems are bound to make a profound impact on our cities. The impact will not only be on the physical setup of our cities but also in how our cities operate and achieve system-level objectives (e.g., livability, resilience, and so on). In order to ensure that cities advance in keeping with the values and aspirations of their key stakeholders (i.e., residents, businesses, and so on), it will be vital for us to ensure that AI systems are designed take on a value-sensitive design approach [170]. AI systems will need to account for the multiple aspects of diversity that are omnipresent in our cities. In addition, these systems will need to possess a degree of transparency, adaptability (to respond to varying environmental conditions), and accountability (for levels of performance). Doing so is non-trivial, but paramount to achieving responsible innovation in the context of AI and cities.

While advances in computational science and technologies will continue to progress at an astounding rate, the level of impact they will have on our future cities comes down to the level of trust individuals and organizations place in these systems. As we continue to live through times where levels of trust in government are at an all-time low [171], planners and public managers needs to consider how social license [172] impacts their ability to deploy emerging technologies. Engaging stakeholders into the design processes when it comes to AI-systems will be critical. Stakeholders should be allowed to shape the elements of these systems and their expected deployment trajectories. Engaging stakeholders will also enable a city to increase the overall knowledge of the community when it comes to the innovative potential of these technologies. To date, we have limited frameworks on how to engage many diverse stakeholders, who have varying knowledge of the intricacies of AI systems, into design processes for urban innovation [173].

We need to enable multiple stakeholders to contribute their technology solutions. Cities need to build platforms that promote the co-creation and sharing of technology solutions [174,175]. While cities have embraced the notion of open data [176] and have created periodic programs to source innovation from external stakeholders (e.g., Hackathons) [177], much more is needed when it comes to designing platforms for co-creation in the context of AI technologies. Stakeholders can be engaged in the auditing of algorithms that underlie AI applications. In addition, they can provide feedback on the performance of these systems, and identify critical choke points. As an example, consider the following innovation by a resident in Berlin, who was able to create traffic jam alerts on Google Maps by slowly moving 99 phones with location services turned on around the city [178]. Residents, such as this individual, enable us to see the limits of AI technologies and their failure points. Such perspectives are critically important as we infuse and design next-generation smart urban technologies.

AI systems will impact cities at multiple levels, from the individual, to the local community (the residents), the neighborhood to the organizational (the city), and even the ecosystem (the city is connected to other cities) level. Impacts at the local level, will have effects up and down the hierarchy. Consider the case of algorithms used to promote sharing economy platforms (e.g., Uber, Lyft, AirBnB, and so on). These algorithms not only provide opportunities to individuals to earn rent on their assets and fees for their services, they also impact zoning rules, they impact the use of established public transport networks, they in turn impact the creation of new service opportunities for existing businesses, and even shape the nature of public finances of a city. More effort is needed to understand the cascading effects of AI innovations across the various levels of a city's functions. In addition, the interdependencies between functions and the implications for overall objectives (i.e., ensuring that local optimization does not compromise global performance) is also critical.

From a design perspective, research on how to design AI technologies in a more agile [179] and frugal [180,181] manner is of critical importance. The public sector has a notorious record of accomplishment when it comes to managing, and delivering on, information systems projects [182]. Cities around the world have had to contend with failed deployments of information system projects that has wasted significant public resources. The study by Desouza et al. [183] provides examples of both success and failure factors of technology-driven smart city attempts, including AI.

Given the significance of technology investments in our cities, we need to see vast improvements in projects management to deliver on their intended value. In this regard, two considerations are critical. First, we must build technologies that are agile, i.e., they have the ability to adopt, adjust, and have the capacity for transformation under changing environmental conditions. Second, we must build technologies in a manner that is in keeping with frugal engineering. Doing so will require us to move away from mega-scale smart cities projects and reconsider the issue of scale. Today, a dominant design paradigm is to build AI technologies that can scale and promote the re-use of components. This thinking is outdated. Today, it is possible to build technologies that work for specific contexts, in an agile and frugal manner, to promote personalization to a specific context and purpose [184].

The security of our next-generation urban technologies is of paramount importance. AI technologies, like most technologies, should be secured and this normally takes the form of traditional information security. Technologies that traverse our urban environments are already targets of hackers and have vulnerabilities. For instance, Greenberg [185] highlights a deep flaw in cars that lets hackers shut down safety features. But, even beyond what one thinks of when it comes to traditional security, today, AI-driven systems can cause harm even if they are not hacked. For example, as stressed by the BBC [186], China coronavirus misinformation spreads online about its origin and scale, i.e., AI inspired platforms that are used for different urban functions can also be manipulated to spread fake news. Cities need to be aware of this as they use these platforms to share information on urban functions, such as the use of social media to engage with citizens. For instance, as reported by Martinez [187], “Rumors of child abductors spread through WhatsApp in a small town in Mexico . . . . The rumors were fake, but a mob burned two men to death before anyone checked.” Likewise, as we have discussed earlier, cities have had their information systems been held for ransom. The incidents will only increase as cities infuse more technologies into their environments. Hence, there is a need for research to examine the security and risk implications of AI-enabled system deployments.

The success of AI deployment to make our cities smarter will depend on the knowledge and care with which such technologies are deployed responsibility and in keeping with our public values. If done well, AI can help us tackle some our most complex urban challenges. However, it can also make our cities more fragile [54]. As stated by Stephen Hawking on the BBC, “The development of full artificial intelligence could spell the end of the human race. It would take off on its own, and re-design itself at an ever-increasing rate. Humans, who are limited by slow biological evolution, couldn’t compete, and would be superseded.”

On that very point, Gherhes and Obrad [188] report the findings of their study on technical and humanities student perspectives on the development and sustainability of AI. The study discloses that out of 928 participants 58.3% considers that AI will have a positive influence on the society. On the other hand, the percentage of those confessing to being confused or concerned is also quite significant (41.7%). The probability that AI might destroy humankind and replace people in certain activities and jobs are among the greatest fears [188].

As the AI applications are becoming more common, there grows the skepticism on the misuse of the technology. For example, most recently the Clearview AI facial recognition system has generated major concerns on the privacy issues. Australian police have been using this unaccountable facial recognition service that combines machine learning and wide-ranging data gathering practices to identify members of the public from online photographs. As stated by Golenfein [189] “Beyond the ethical arguments around facial recognition, Clearview AI reveals Australian law enforcement agencies have such limited technical and organizational accountability that we should be questioning their competency even to evaluate, let alone use, this kind of technology". Similarly, the New South Wales state government of Australia is using AI to spot drivers with mobile phones (often mixed phones with other rectangular items), and the Australian government welfare agency Centrelink is using AI (often incorrectly) to issue debt notices to welfare recipients [190].

Furthermore, scholars warn us of the possible risks of advanced AI. For instance, these risks range from unsafe recommendations for treating illnesses [191] to fatal autonomous car accidents [192], and from racist chatbots [193] to social manipulation [194]. While various dystopian futures have been advanced, including those in which humans eventually become obsolete, with the subsequent extinction of the human race, [195] put forward the following scenarios to think about the ways to protect us from the risks of advanced AI: (a) An AI system tasked with preventing HIV decides to eradicate the problem by killing everybody who carries the disease, or one tasked with curing cancer decides to kill everybody who has any genetic predisposition for it; (b) An autonomous AI military drone decides the only way to guarantee an enemy target is destroyed is to wipe out an entire community, and; (c) An environmentally protective AI decides the only way to slow or reverse climate change is to remove technologies and humans that induce it.

Lastly, abovementioned challenges also relate to the specific characteristics of AI technologies that include opacity ('black box-effect'), complexity, unpredictability and partially autonomous behavior, may make it hard to verify compliance with and may hamper the effective enforcement of rules of existing laws meant to protect fundamental rights [196]. In order to address this issue, the [197] white paper entitled 'Artificial intelligence: a European approach to excellence and trust' underlined the following seven key requirements for a successful AI utilization: (a) Human agency and oversight; (b) Technical robustness and safety; (c) Privacy and data governance; (d) Transparency; (d) Diversity, non-discrimination, and fairness; (e) Societal and environmental well-being, and; (f) Accountability. On that very point, Salmon et al. [195] propose the immediate application of the following three sets of controls for AI development and testing: (a) The controls required to ensure AI system designers and developers create safe AI systems; (b) The controls that need to be built into the AIs themselves, such as 'common sense', morals, operating procedures, decision-rules, and so on, and; (c) The controls that need to be added to the broader systems in which AI will operate, such as regulation, codes of practice, standard operating procedures, monitoring systems, and infrastructure. As Elon Musk stated, "we need to regulate AI to combat an 'existential threat' before it's too late" [198]. Fortunately, we are not short of ideas and plans to tackle these issues, and now is the time to implement them before it is too late [199].

6. Conclusions

The study reported in this paper offers a novel contribution to the literature by mapping out the scientific landscape of the understudied 'AI and the smart city' area. This study helps not only in identifying the current and potential contributions of AI to the development of smarter cities—to aid urban policymakers, planners and researchers—, but also in determining the gaps in the literature to bridge them in prospective studies. The study also gives a heads up for urban policymakers, planners and scholars for them to prepare for the disruptions that AI will cause in our cites, societies and businesses [200].

The broad findings of our systematic literature review findings reveal that: (a) AI has an evident potential—but only if utilized responsibly [201]—to provide a positive change in our cities, societies, and businesses by promoting a more efficient, effective and sustainable transition/transformation [202,203], and; (b) Particularly, AI, with its technology, algorithms, and learning capabilities, can be a useful vehicle in automating the problem solving and decision-making processes that, in return, could reform urban landscapes and support the development of smarter cities [62].

The specific findings of our systematic literature review disclose that: (a) AI in the context of smart cities is an emerging field of research and practice; (b) The central focus of the literature is on AI technologies, algorithms, and their current and prospective applications; (c) AI applications in the context of smart cities mainly concentrate on business efficiency, data analytics, education, energy, environmental sustainability, health, land use, security, transport, and urban management areas; (d) There is limited scholarly research investigating the risks of wider AI utilization, and; (e) Upcoming disruptions of AI on cities and societies have not been adequately investigated in the literature.

AI provides a new hope for addressing some of the urbanization problems we failed to solve due to the complexities involved. Nevertheless, AI is not a silver bullet. While we are currently far away from such advance application of AI, there are numerous contributions of the rapidly developing technology for our cities and societies. Some of these contributions are presented in the paper and some warnings have been made for the good use of the technology. While there is a promise of the emerging advanced technologies, such as AI, our rapid urbanization, industrialization, and globalization practices are perhaps making even technology struggle with coming up solution. The recent anthropogenic climate change triggered environmental catastrophes and disasters—such as 2020 Australian Bushfires—and urbanization and globalization triggered epidemics—such as COVID-19—require more than technology for them not to be repeated again.

The paper opened with a viewpoint on technocentric solutions being widely seen as remedies for global issues—including climate change and urbanization problems. Indeed, AI and other technologies will definitely equip us with better data analytics and prediction models in more efficient and effective ways. To date, there are two different approaches to AI: rules-based (coded algorithms of if-then statements that are basically meant to solve simple problems) and learning-based (diagnoses problems by interacting with the problem), where both AI approaches have valid use cases when it comes to studying the environment and solving climate change. In other words, when it comes to helping solve climate change, a learning-based AI could essentially do more than just crunch CO_2 emission numbers, where a learning-based AI could actually record those numbers, study causes and solutions, and then recommend the best solution [204]—'in theory'. We say 'in theory', because "fully functioning AI systems do not yet exist, and it has been estimated that they will be with us anywhere between 2029 and the end of the century" [195].

While we do not disagree with the positive contributions of technological prescriptions—such as AI and other urban technologies—[205], we close the paper with the following quote by Andrew Ng, co-founder and lead of Google Brain. "Much has been written about AI's potential to reflect both the best and the worst of humanity. For example, we have seen AI providing conversation and comfort to the lonely; we have also seen AI engaging in racial discrimination. Yet the biggest harm that AI is likely to do to individuals in the short term is job displacement, as the amount of work we can automate with AI is vastly bigger than before. As leaders, it is incumbent on all of us to make sure we are building a world in which every individual has an opportunity to thrive."

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Appendix A

Table A1. Analysis Highlights of the Reviewed Literature.

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Abduljabbar et al. [98]	Applications of artificial intelligence in transport	Sustainability	To provide an overview of AI techniques applied to transport.	Advocates that AI in the transport field is aimed at decreasing VKT thus reducing emissions and other environmental degradation.	Environment	LB KB PM ML EI SO	ES DN NN DAI EA	FS DL SI GA	Smart Transport
Ajerla et al. [99]	A real-time patient monitoring framework for fall detection	Wireless Communications and Mobile Computing	To develop a framework that uses edge computing to send data from wearable devices.	Describes the use of machine learning in improving fall detection devices.	Society	PM ML	NN CV	AR	IoT Smart Health
Alam et al. [77]	Data fusion and IoT for smart ubiquitous environments	IEEE Access	To review existing literature on data fusion and IoT with a focus on mathematical models.	Discusses the benefits of AI in relation to data fusion.	Economy	LB KB PM ML SO	ES DN NN EA	FS BN DL GA	IoT
Allama & Dhunny [100]	On big data, artificial intelligence and smart cities	Cities	To provide information on the use of AI and big data in smart cities.	Provides insights regarding the application of AI to public safety and security.	Governance	LB KB PM ML	ES NN	FS	IoT
Alsamhi et al. [101]	Survey on collaborative smart drones and internet of things for improving smartness of smart cities	IEEE Access	To show how drones and IoT can improve the smartness of cities.	Provides insights into how autonomous drones can be used for security, safety measures.	Governance	PM ML SO	NN CV EA	AR IR MV GA	IoT Drones
Altulyan et al. [149]	A unified framework for data integrity protection in people-centric smart cities	Multimedia Tools and Applications	To address data integrity from an end-to-end perspective.	Describes how block chain and fog computing can be used to manage data integrity.	Economy	n/a	n/a	n/a	IoT
Alzoubi et al. [102]	Prediction of environmental indicators in land levelling using artificial intelligence techniques	Journal of Environmental Health Science and Engineering	To develop AI techniques in land levelling.	Discusses using AI in land levelling.	Environment	ML	NN	n/a	n/a
Bajaj & Sharma [82]	Smart education with artificial intelligence-based determination of learning styles	Procedia Computer Science	To develop a framework for student learning styles using learning models and ratification intelligence.	Develops a framework for AI to improve adaptivity in teaching.	Society	LB KB PM ML EI SO	ES DN PP NN DAI EA	FS BN BPS MAS SI GA	Smart Education
Bennett & Hauser [137]	Artificial intelligence framework for simulating clinical decision-making	Artificial Intelligence in Medicine	To developing a framework for using AI to address healthcare challenges.	Describes how AI could lead to improvements in diagnosis and treatment.	Society	PM EI	DAI	MAS	Smart Health

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Bose [78]	Artificial intelligence techniques in smart grid and renewable energy systems	Proceedings of the IEEE	To explain application of AI in smart grids and renewable energy systems	Provides insights into the use of smart grids for prediction, estimation and control of power systems.	Environment	LB KB ML	ES NN AS	FS DL	Smart Energy
Brady [103]	The challenge of big data and data science	Annual Review of Political Science	To identify innovative methods for answering previously hard-to-tackle questions about society.	Provides insights into how AI can improve decision-making, efficiency, and reduce errors and uncertainty.	Economy	ML	NN	n/a	n/a
Braun et al. [83]	Security and privacy challenges in smart cities	Sustainable Cities and Society	To identify possible solutions to five smart city challenges.	Provides insights into the use of AI for cyber security.	Governance	ML	NN	n/a	Smart Surveillance
Bui & Jung [104]	Computational negotiation-based edge analytics for smart objects	Information Sciences	To develop a computational negotiation approach on IoT systems where distributed edge devices can make their own decisions.	Describes the potential for AI and smart traffic control systems to communicate with connected-AV, and make real-time decisions to improve the efficiency of the transport network.	Economy	ML EI	AS	n/a	IoT
Cai et al. [105]	Deep learning-based video system for accurate and real-time parking measurement	IEEE Internet of Things Journal	To develop an accurate and real-time video system for future IoT and smart cities applications	Discusses using AI for real-time measurements to make parking more efficient.	Environment	ML	NN	DL	IoT Smart Parking
Casares [84]	The brain of the future and the viability of democratic governance	Futures	To identify AI implications and the potential challenges in democratic societies.	Identifies the potential for AI to contribute to public governance.	Governance	ML	NN	DL	n/a
Castelli et al. [144]	Predicting per capita violent crimes in urban areas	Journal of Ambient Intelligence and Humanized Computing	To combine a version of genetic programming with a local search method	Describes the use of AI in crime prediction and optimal allocation of law enforcement.	Governance	SO	EA	GA	n/a
Chassignol et al. [85]	Artificial Intelligence trends in education	Procedia Computer Science	To identify the prospective impact of AI technologies on the study process.	Identifies the potential for AI to develop innovative teaching methods, and improve student outcomes.	Society	ML	NN	n/a	Smart Education Augment. Reality Virtual Reality
Chatterjee et al. [164]	Success of IoT in smart cities of India	Government Information Quarterly	To combine IoT with AI in smart machines to simulate intelligent behavior and assist autonomous decision making.	Describes the use of AI to obtain data from IoT to understand acceptance of new technologies.	Governance	n/a	n/a	n/a	IoT ICT

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Chau [69]	A review on integration of artificial intelligence into water quality modelling	Marine Pollution Bulletin	To reviewing the current state-of-the-art AI and its application in water quality modelling.	Provides insights into how AI can be used to develop more accurate water quality modelling	Environment	LB KB ML SO	ILP ES NN EA	FS DL GA	Smart Environment
Chen et al. [107]	An intelligent robust networking mechanism for the internet of things	IEEE Communications Magazine	To enhance the robustness of IoT topologies	Identifies how AI can reduce uncertainty in relation to robustness optimization, improve the cost and efficiency of network communications and protect against cyber-attacks.	Economy	ML SO	NN EA	DL GA	IoT Smart Energy
Chen et al. [106]	Cognitive-LPWAN	IEEE Transactions on Green Communications and Networking	To provide information regarding current wireless communication technologies, and other technologies	Provides insights into how AI can be used to improve communication networks	Economy	ML	NN	DL	IoT
Chmiel [74]	INSIGMA	Multimedia Tools and Applications	To investigate using intelligent transport systems for improving safety, mobility and environmental outcomes.	Describes using intelligent transport systems to improve congestion.	Environment	PM ML	CV	IR MV	Smart Transport
Chui et al. [86]	Energy sustainability in smart cities	Energies	To show ways in which AI can support energy sustainability.	Provides insights in the use of AI to monitor energy consumption.	Environment	ML SO	EA	GA	IoT Smart Energy
Cortes et al. [136]	Artificial intelligence and environmental decision support systems	Applied intelligence	To provide an overview of the impact of AI on environmental decision support systems.	Identifies how AI can assist in environmental decision-making	Environment	LB KB PM	Expert System DN	n/a	Smart Environment
Cui et al. [108]	Big data analytics and network calculus enabling intelligent management of autonomous vehicles in a smart city	IEEE Internet of Things Journal	To develop a new online AV fleet management scheme that controls congestion in cities.	Discusses using AI to reduce travel time in AV.	Environment	ML	n/a	n/a	IoT Smart Transport
De Paz et al. [75]	Intelligent system for lighting control in smart cities	Information Sciences	To develop a new intelligent lighting system for cities.	Describes the use of AI to control public lighting to optimize power usage.	Environment	PM ML EI	CV NN DAI	IR MV MAS	Smart Energy

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Desouza et al. [109]	Designing, developing, and deploying artificial intelligence systems	Business Horizons	To reflect and provide insights from AI projects in the public sector.	Discusses how cognitive computing systems are able simulate human thought and learning and can be used for fraud detection, decision-support, and online assistance.	Governance	ML	NN	DL	n/a
Devedzic [147]	Web intelligence and artificial intelligence in education	Educational Technology & Society	To survey important aspects of web intelligence in the context of AI in education	Discusses how AI can improve adaptability in learning environments, and create more comfortable learning environments.	Society	EI	DAI	ABM	Smart Education
Din et al. [110]	Machine learning in the internet of things	Future Generation Computer Systems	To examine different IoT based machine learning mechanisms	Identifies machine learning as an important component for IoT particularly regarding data management.	Economy	ML	NN	DL	IoT
Dobrescu & Dobrescu [87]	Artificial intelligence (AI)	Global Economic Observer	To present trends, analyses and perceptions of AI.	Presents the benefits and disadvantages of integration of AI into all areas of socio-economic life	Society	PM ML	NLP CV NN	DL IR NLU NLG	n/a
Dong et al. [111]	Energy-efficient fair cooperation fog computing in mobile edge networks for smart city	IEEE Internet of Things Journal	To examine the convexity of the optimization problem and design a fairness cooperation algorithm.	Identifies IoT and AI as two of the most important technologies to help enable smart cities particularly regarding big data analysis.	Economy	ML	n/a	n/a	IoT
Drigas & Ioannidou [71]	Artificial intelligence in special education	International Journal of Engineering Education	To review studies that use AI methods in making accurate diagnosis.	Discusses how AI can stimulate problem solving, particularly in special needs students, to enhance the way children interact with their environment.	Society	LB KB ML	ES NN	FS	Smart Education
Edwards et al. [88]	I, teacher: using artificial intelligence (AI) and social robots in communication and instruction	Communication Education	To argue the importance of using AI in teaching.	Examines the role of teacher in an AI enabled education system.	Society	ML	NLP	NLG	Social Robots Smart Education

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Eldrandaly et al. [148]	PTZ-surveillance coverage based on artificial intelligence for smart cities	International Journal of Information Management	To develop AI algorithm for adjusting the orientation of pan-tilt-zoom surveillance cameras.	Discusses the use of AI technology to automatically improve the field of view of surveillance cameras	Governance	EI	DAI	SI	IoT Smart Surveillance
Falco et al. [162]	A master attack methodology for an AI-based automated attack planner for smart cities	IEEE Access	To identify solutions for cyber safety of critical infrastructure.	Identifies the potential for automated tools to evaluate cyber threats to infrastructure.	Governance	n/a	n/a	n/a	IoT
Feng & Xu [63]	Hybrid artificial intelligence approach to urban planning	Expert Systems	To present a hybrid AI system for use in urban planning.	Describers how AI can assist with knowledge-based decision making.	Environment	LB KB ML	ES NN	FS DL	n/a
Fernández et al. [138]	An intelligent surveillance platform for large metropolitan areas with dense sensor deployment	Sensors	To maximize the number of deployable units in surveillance while minimizing costs.	Presents an intelligent surveillance platform for surveillance of public spaces	Governance	PM	CV	IR	Smart Surveillance
Garlík [79]	The application of artificial Intelligence in the process of optimizing energy consumption in intelligent areas	Neural Network World	To monitor and control the operation of selected smart objects.	Discusses the use of AI for energy optimization	Environment	ML SO	NN EA	GA	Smart Energy
Guilherme [153]	AI and education	AI & Society	To identify use of AI in assessing education and the relations between teachers and students, and students and students.	Identifies new roles for teachers in education.	Society	n/a	n/a	n/a	Smart Education
Guo & Li [89]	The application of medical artificial intelligence technology in rural areas of developing countries	Health Equity	To review the literature concerning the prospects of medical AI technology, and application in rural areas.	Identifies AI as a means to improve equality between rural and urban health areas.	Society	ML	NN	n/a	Smart Health
Guo et al. [90]	Artificial intelligence-based semantic internet of things in a user-centric smart city	Sensors	To discuss the links between AI and IoT in the context of smart city	Describes how AI can contribute to environmental monitoring.	Environment	PM ML	DN NN	BN DL	IoT
Håkansson [91]	Ipsum: an approach to smart volatile ICT-infrastructures for smart cities and communities	Procedia Computer Science	To create smart volatile ICT infrastructures in cities.	Discusses using AI for customized health care.	Society	ML	n/a	n/a	IoT ICT Cyber-Physical Smart Infrastructure

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Hanson & Marshall [67]	Artificial intelligence applications in the intensive care unit	Critical Care Medicine	To review application of AI in intensive care.	Describes how AI as a monitoring tool can assist intensive care providers and resulting in reduced costs and improved patient outcomes	Society	LB KB ML SO	ES NN EA	FS DL GA	Smart Health
Hariri et al. [112]	Uncertainty in big data analytics	Journal of Big Data	To review big data analytics.	Identifies AI techniques as beneficial to the accurate and timely analysis of big data.	Economy	LB KB PM ML SO	ES DN EA	FS BN	IoT
Ibrahim et al. [113]	URBAN-i: from urban scenes to mapping slums, transport modes, and pedestrians in cities using deep learning and computer vision	Environment and Planning B	To develop framework for multipurpose realistic-dynamic urban modelling using deep CNN	Describes using deep learning to differentiate spatial structures.	Environment	PM ML	CV NN	IR DL	n/a
Inclezan & Prádanos [156]	Overview: a critical view on smart cities and AI	Journal of Artificial Intelligence Research	To advocate using AI to solve urban problems.	Reflects, critically, on the optimistic viewpoint of AI in relation to its potential to respond to urban problems (e.g. congestion, population growth, energy efficiency, environmental degradation and safety).	Environment	n/a	n/a	n/a	n/a
Iqbal et al. [114]	Intelligent remote monitoring of parking spaces using licensed and unlicensed wireless technologies	IEEE Network	To develop an intelligent parking system model	Describes using AI for parking utilization and optimization.	Environment	PM ML	CV NN	AR IR MV DL	IoT Smart Parking
Jha et al. [80]	Renewable energy	Renewable and Sustainable Energy Reviews	To summarize reviews and state-of-the-art research outcomes related to renewable energies	Describes the use of AI to achieve renewable energy goals	Environment	PM ML EI SO	DN PP NN DAI EA	BN BPS GA MAS SI	Smart Energy
Khalifa [161]	Smart cities: opportunities, challenges, and security threats	Journal of Strategic Innovation and Sustainability	To discuss the importance and consequences of smart city development.	Identifies the opportunity for AI and smart cities to achieve better security measures	Governance	n/a	n/a	n/a	n/a
Kopytko et al. [92]	Smart home and artificial intelligence as environment for the implementation of new technologies	Path of Science	To determine smart homes and AI as combined innovative tools.	Provides insights into the use of AI in smart homes to achieve energy savings.	Environment	LB KB ML SO	ES NN DAI EA	FS DL MAS GA	IoT Smart Homes

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Kundu [115]	Blockchain and trust in a smart city	Environment and Urbanization Asia	To provide insights into institutions that can be governed on blockchain through smart contracts.	Identifies trust as a fundamental part of smart city governance.	Governance	ML	n/a	n/a	IoT Blockchain
Le et al. [116]	A comparative study of PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN in estimating the heating load of buildings' energy efficiency for smart city planning	Applied Sciences	To propose four new AI techniques for forecasting the heating load of buildings	Discusses the use of AI to improve energy efficiency in buildings	Environment	ML EI SO	NN DAI EA	DL SI GA	Smart Energy
Leung et al. [117]	AI-based sensor information fusion for supporting deep supervised learning	Sensors	To present an AI-based system which supports deep supervised learning of transport data collected from sensors	Describes using AI-based sensor to collect data from multiple sources.	Environment	ML	NN	DL	IoT GNS GPS GIS
Li et al. [118]	Intelligent metasurface imager and recognizer	Light: Science & Applications	To propose the use of a smart metasurface imager and recognizer, empowered by a network of ANN to control data flow	Identifies the potential for AI enabled sensors and other devices to monitor health.	Society	ML	NN CV	DL MV	IoT Smart Surveillance
Liu et al. [93]	Object tracking in vary lighting conditions for fog based intelligent surveillance of public spaces	IEEE Access	To improve the robustness and accuracy of the correlation filter-based trackers for handling intense illumination change.	Describes the use of intelligent surveillance systems in detecting abnormal circumstances, identifying and tracking targets.	Governance	PM ML	CV	AR IR MV	Smart Surveillance
Liu et al. [119]	Modeling and simulation of robot inverse dynamics using LSTM-based deep learning algorithm for smart cities and factories	IEEE Access	To highlight the influence of the hyper-parameter settings on model performance and to explore the applicability of the Long Short-Term Memory model.	Develops a model that uses deep learning to make robots more responsive to uncertainty.	Economy	ML	NN	DL	Robotics
Lukowicz & Slusalle [94]	How to avoid an AI interaction singularity	Interactions	To advocate for AI systems to focus on enhancing human cognitive capabilities, and develop creativity, inventiveness, and intuition, trust, ethics, and values	Discusses goals required to improve AI decision-making.	Economy	PM ML	CV NLP	IR NLU	n/a

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Lytras et al. [120]	Data analytics in smart healthcare	Applied Sciences	To identify use of AI to improve quality of life and relieve medical shortages	Describes how smart healthcare analytics can improve quality of life for patients.	Society	ML	NN	DL	IoT Smart Health
Martins [95]	Towards smart city innovation	Revista de Tecnologia da Informação e Comunicação	To analyze the impact and perspectives on adopting software-defined networking and AI for smart city projects.	Describes how cognitive processing could allow innovative solutions to complex problems.	Governance	ML	NN	DL	n/a
McArthur et al [140]	The roles of artificial intelligence in education	Journal of Educational Technology	To summarize current applications of ideas from Al to education field.	Identifies future uses of AI in the education field.	Society	LB KB	ES	n/a	Smart Education
Meena et al. [145]	Mobile power infrastructure planning and operational management for smart city applications	Energy Procedia	To maximize the profit of utility and electric vehicle owners.	Provides insights into the use of AI to optimize energy consumption particularly electrical vehicles.	Environment	SO	EA	GA	IoT
Muhammad et al. [121]	Intelligent and energy-efficient data prioritization in green smart cities	IEEE Communications Magazine	To highlight the key challenges of data prioritization, its future requirements, and propositions for integration into green smart cities	Discusses the use of AI to improve the efficiency of data prioritization.	Environment	ML	NN	DL	IoT
Nápoles et al. [96]	MUSA–I: towards new social tools for advanced multi-modal transportation in smart cities	Multidisciplinary Digital Publishing Institute Proceedings	To describe the general architecture and current implementation of an explicit multi-modal transport demand system for smart cities.	Discusses using AI for transport demand management.	Environment	PM ML	CV	AR IR MV	Smart Transport
Neuhauser et al. [142]	Using design science and artificial intelligence to improve health communication	Patient Education and Counselling	To describe how the use of AI can improve the effectiveness of health communication.	Discusses how AI can improve the effectiveness of communication in health settings.	Society	LB KB	ES	n/a	Smart Health
Noorbakhsh-Sabet [122]	Artificial intelligence transforms the future of healthcare	The American Journal of Medicine	To review the applications for machine learning in healthcare.	Identifies AI potential to increase learning and decision support in the health sector.	Society	ML	NN	DL	Smart Health

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Park et al. [123]	Dependable fire detection system with multifunctional artificial intelligence framework	Sensors	To propose new fire detection system using a multifunctional AI framework and data transfer delay minimization mechanism.	Describes how machine learning can improve fire detection systems.	Governance	ML	NN	DL	IoT Smart Fire Detection
Patel et al. [70]	The coming of age of artificial intelligence in medicine	Path of Science	To analyze discussions which reflect on AI in the medical research field.	Discusses the use of AI in medical care.	Society	KB PM ML EI	ES DN NN DAI	BN ABM	Smart Health
Pence [152]	Artificial intelligence in higher education	Journal of Educational Technology Systems	To explore the use of AI in education	Identifies the need for education to be adaptive in the face of rapid technology advances, and changes to employment.	Society	n/a	n/a	n/a	n/a
Pieters [141]	Explanation and trust	Ethics and Information Technology	To investigate the relationship between explanation and trust in the context of AI	Describes the importance on online security for trust in AI systems.	Governance	LB KB	ES	n/a	n/a
Ponce & Gutiérrez [124]	An indoor predicting climate conditions approach using internet-of-things and artificial hydrocarbon networks	Measurement	To predict the temperature of remote locations using field sensors and information from network.	Identifies methods of incorporating AI in weather monitoring to better predict changes.	Environment	ML	NN	n/a	IoT Artificial Hydrocarbon Networks
Puri et al. [125]	Hybrid artificial intelligence and internet of things model for generation of renewable resource of energy	IEEE Access	To develop an IoT based system to generate electrical energy from multiple sensors.	Provides insights into the use of piezoelectric sensors to generate energy from body heat.	Environment	ML	NN	n/a	IoT Smart Energy
Quan et al. [146]	Artificial intelligence-aided design	Environment and Planning B	To develop a smart design framework which uses AI to assist urban design decision-making.	Provides insights into the use of AI in the design process	Environment	SO	EA	GA	Smart Design
Rahman et al. [126]	Blockchain and IoT-based cognitive edge framework for sharing economy services in a smart city	IEEE Access	To propose blockchain-based infrastructure to support security- and privacy-oriented spatio-temporal smart contract services.	Identifies benefits of AI in helping with data collection, fusing information from multiple sources.	Economy	ML	NN	DL	IoT Blockchain

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Ramesh et al. [68]	Artificial intelligence in medicine	Annals of The Royal College of Surgeons of England	To explore the proficiency of AI in medicine.	Provides insights into how AI can help with the analysis of complex medical data.	Society	LB KB ML SO	ES NN EA	FS DL GA	Smart Health
Reaz [73]	Artificial intelligence techniques for advanced smart home implementation	Acta Technica Corvininesis-Bulletin of Engineering	To develop a platform which serves as a reference point for developing more cutting-edge smart home technologies.	Identifies how AI can be used to provide more efficient power consumption	Environment	LB KB PM ML EI	ES CV NN AS DAI	FS AR MAS	Smart Home
Rho et al. [72]	Advanced issues in artificial intelligence and pattern recognition for intelligent surveillance system in smart home environment	Engineering Applications of Artificial Intelligence	To review topics strongly related to the intelligent surveillance systems in smart homes.	Describes the use of AI in home surveillance systems	Governance	ML	n/a	n/a	Smart Surveillance Smart Homes
Roll & Wylie [143]	Evolution and revolution in artificial intelligence in education	International Journal of Artificial Intelligence in Education	To review papers to identify the focus and typical scenarios that occupy the field of AI and education.	Describes how AI will impact the job market and create effective educational system.	Society	LB KB	ES	n/a	Smart Education
Ruohomaa et al. [127]	Towards smart city concept in small cities	Technology Innovation Management Review	To present the practical viewpoints, cases and experiences relating to the planning of smart cities.	Identifies shared learning and cooperation as important factors in increasing innovation and growth in smart cities.	Economy	ML	n/a	n/a	IoT
Sgantzos & Grigg [128]	Artificial intelligence implementations on the blockchain	Future Internet	To reveal the potential combined applications of AI and blockchain.	Describes the potential for AI to be an independent source of knowledge and innovation.	Economy	ML EI SO	NN DAI EA	MAS GA	IoT Blockchain
Shi et al. [129]	Smart textile-integrated microelectronic systems for wearable applications	Advanced Materials	To provide an overview of the progress of the smart textile field.	Describes the use of smart textiles for health care monitoring.	Society	ML	NN	n/a	Smart Textiles
Soomro et al. [130]	Smart city big data analytics	Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery	To present classification model that studies four aspects of research in the big data analytics domain.	Provides insights into the potential for machine learning to complete complex statistical analysis and make more informed decisions.	Economy	ML SO	NN EA	GA	n/a

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Stefanelli [139]	The socio-organizational age of artificial intelligence in medicine	Artificial Intelligence in Medicine	To explore the great challenges for AI in medicine.	Identifies AI as an effective way to manage medical knowledge, and increase resources for patient care.	Society	KB	n/a	n/a	Smart Health
Streitz [131]	Beyond 'smart-only' cities: redefining the 'smart-everything' paradigm	Journal of Ambient Intelligence and Humanized Computing	To present the various manifestations of the smart everything paradigm.	Identifies the need for privacy-by-design to empower people and enforce a citizen centric approach to data collection.	Governance	ML	NN	DL	IoT
Syifa et al. [132]	An artificial intelligence application for post-earthquake damage mapping in Palu, Central Sulawesi, Indonesia	Sensors	To develop a classification of pre- and post-earthquake satellite images using ANN and support vector machine classifiers.	Provides insights into the use of AI subsets artificial neural networks and support vector machine classifiers to identify areas affected by earthquakes	Governance	ML	NN	n/a	n/a
Wan & Hwang [97]	Value-based deep reinforcement learning for adaptive isolated intersection signal control	IET Intelligent Transport Systems	To identify the use of reinforcement learning in signal controls.	Describes using traffic signal control methods for transport system optimization.	Environment	PM ML	PP NN	DL	Smart Transport
Wang & Srinivasan [81]	A review of artificial intelligence-based building energy use prediction	Renewable and Sustainable Energy Reviews	To better understand of the use of ensemble models for predicting building energy use.	Discusses the use of AI in building use energy predictions.	Environment	PM ML	PP NN	n/a	n/a
Wang et al. [133]	Exploring the application of artificial intelligence technology for identification of water pollution characteristics and tracing the source of water quality pollutants	Science of The Total Environment	To develop an AI scheme for identifying spatiotemporal water quality distributions and the relationships between water quality indicators and industrial point sources of pollutants.	Identifies the potential for AI to monitor water pollutant levels and changes	Environment	ML	NN	DL	Smart Environment
Wei et al. [134]	Conventional models and artificial intelligence-based models for energy consumption forecasting: a review	Journal of Petroleum Science and Engineering	To review conventional models and AI based models in energy consumption forecasting.	Describes how Ai can be used in energy forecasting to assist with identifying inefficiencies in energy consumption and pollution prevention.	Environment	PM ML EI SO	DN NN DAI EA	BN DL SI GA	Smart Energy
Wogu et al. [135]	Artificial intelligence, smart classrooms and online education in the 21st century	Journal of Cases on Information Technology	To investigate impact of AI innovations in the education sector and on human development	Describes the potential changes AI will bring to the education sector.	Society	ML	n/a	n/a	Smart Education

Table A1. *Cont.*

Author	Title	Journal	Aim	Relevance	Domain	Paradigm	Application	Method	Technology
Wu & Silva [26]	Artificial intelligence solutions for urban land dynamics	Journal of Planning Literature	To increase understanding of how AI approaches urban and land dynamics modelling processes.	Discusses the use of AI in identifying the dynamics of urban land use.	Environment	KB ML EI SO	ES NN DAI EA	FS ABM SI GA	n/a
Yu et al. [150]	Decentralized big data auditing for smart city environments leveraging blockchain technology	IEEE Access	To design a blockchain instantiation and conduct a comparison between the existing and proposed schemes.	Identifies the potential for AI to processing and analyzing large amounts of data	Economy	n/a	n/a	n/a	Blockchain
Yun et al. [76]	Not deep learning but autonomous learning of open innovation for sustainable artificial intelligence	Sustainability	To build an interaction model between direct and autonomous learning.	Investigates the potential for AI to develop autonomous learning capabilities.	Economy	ML EI	AS DAI	SI	n/a
Zou et al. [157]	Exploring urban population forecasting and spatial distribution modeling with artificial intelligence technology	Computer Modeling in Engineering & Sciences	To improve the precision of small area population forecasting.	Describes the use of AI in population forecasting	Environment	n/a	n/a	n/a	n/a

Notes: n/a= not available as not identified in the article. AI Paradigms: Logic-based (LB), Knowledge-based (KB), Probabilistic Methods (PM), Machine Learning (ML), Embodied Intelligence (EI), and Search and Optimization (SO). AI Applications: Autonomous Systems (AS), Computer Vision (CV), Distributed Artificial Intelligence (DAI), Decision Networks (DN), Evolutionary Algorithms (EA), Expert Systems (ES), Inductive Logic Programming (ILP), Natural Language Processing (NLP), Neural Networks (NN), and Probabilistic Programming (PP). AI Methods: Agent-Based Modelling (ABM), Activities Recognition (AR), Bayesian Networks (BN), Bayesian Program Synthesis (BPS), Deep Learning (DL), Fuzzy Systems (FS), Genetic Algorithms (GA), Image Recognition (IR), Multi-Agent Systems (MAS)., Machine Vision (MV), Natural Language Generation (NLG), Natural Language Understanding (NLU), and Swarm Intelligence (SI).

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