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Synergizing AI, IoT, and Blockchain for Diagnosing Pandemic Diseases in Smart Cities: Challenges and Opportunities

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Abstract: The advent of smart cities has paved the way for transformative advancements in healthcare, particularly in the domain of disease diagnosis. In the wake of the COVID-19 pandemic, accurate and timely identification of Pandemic diseases has become paramount. This paper explores the challenges and opportunities in synergizing Artificial Intelligence (AI), Internet of Things (IoT), and Blockchain technologies for diagnosis of Pandemic diseases in smart cities. This study provides an overview of each technology and its relevance to sustainable healthcare in smart cities, emphasizing its potential for analyzing medical data and making informed decisions. We also explore how IoT devices can contribute to disease surveillance, enabling real-time data collection and remote healthcare. Additionally, we discuss the potential of Blockchain in ensuring secure and transparent healthcare systems. Following, the paper study the synergistic potential of integrating AI, IoT, and blockchain, emphasizing how their combined strengths can enhance the accuracy, efficiency, and security of COVID-19 diagnosis systems in smart cities Moreover, the paper highlights the challenges in integrating these technologies and the opportunities for research and implementation, underlining the significance of synergizing AI, IoT, and Blockchain in disease diagnosis in smart cities. The findings demonstrate that the convergence of AI, IoT, and blockchain can enhance the speed and accuracy of diagnosing Pandemic diseases, leading to more effective containment and management strategies.

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1. Introduction

Smart cities are a compelling vision of the future, where advanced technologies flawlessly integrate with urban infrastructure to enhance the quality of life for residents. These cities leverage cutting-edge improvements to optimize resource consumption, advance sustainability, and specify effective public services [1]. One critical region where smart cities hold great potential is healthcare. In conventional urban settings, healthcare systems face numerous challenges, incorporating constrained resources, ineffective service supply, and struggles in disease detection and management. Nevertheless, with the advent of smart cities, the healthcare systems are shifting [2]. Various components of healthcare systems, including physicians, hospitals, insurance companies, and pharmacies, are actively exploring the potential of technology-driven solutions within smart cities. Perfect and sensible diagnosis of pandemic diseases in smart cities is of dominant importance because of its potential to save lives, avoid further transmission, and optimize resource distribution. In heavily crowded urban environments, where residents often interact intently, the prompt identification and isolation of infected persons are crucial to curbing the spread of infectious diseases. Through

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leveraging advanced ICT technologies, smart cities can enhance disease surveillance, early detection, and efficient contact tracing, thereby enabling swift intervention measures [5]. Timely diagnosis facilitates prompt medical intervention, enabling healthcare providers to administer appropriate treatments, reduce the severity of illness, and prevent problems. Besides, precise disease diagnosis in smart cities enables data-driven decision-making, empowering policymakers, and healthcare authorities to allocate resources effectively, implement targeted interventions, and protect the well-being of the community at large [6].

Pandemic diseases present numerous challenges when it comes to their diagnosis and management within the healthcare system. Medical facilities become overwhelmed as cases escalate at an alarming rate with limited resources leading to stretched medical staff. Accurate identification is incredibly tricky due to its unpredictable symptoms combined with its similarity to other lung infections which require specific testing equipment and designated facilities [7]. Furthermore, updates must keep coming regularly as this disease progresses continuously over time making it challenging for health care providers who have already been delivering final services in regular circumstances. Moreover, the variation protocols among different health care systems create difficulties in sharing information effectively for proper treatment procedures resulting in delayed assessment times leading up extensive waiting periods before receiving test results; confidentiality issues make matters worse where there aren't many strict protocols established beforehand proving problematic. Therefore, working together as policymakers across all levels can help improve current situations by offering solutions like better diagnostic tools development increasing collaboration opportunities between hospitals around region-specific-based patient needs ensuring smooth data-sharing processes starting from check-ins till post-treatments follow-ups etc.[8-9].

Smart cities usually comprise a set of interconnected networks of sensors, devices, and data analytics to establish a complete healthcare ecosystem that can collect vast amounts of real-time health data, enabling comprehensive and continuous monitoring of population health. This wealth of data, combined with the power of artificial intelligence (AI), Internet of Things (IoT), and blockchain technologies, can make transformative changes in disease diagnosis, avoidance, and medication. AI, with its talent to analyze complicated datasets and recognize patterns, enables healthcare specialists with precise and timely insights [10]. The introduction and improvement of machine learning algorithms enable detecting the patterns indicative of pandemic diseases, allowing for early identification and intervention. On the other hand, IoT devices can have a critical role in enabling permanent monitoring of individuals' health parameters and granting real-time data to healthcare workers. This connectivity enables remote healthcare services, personalized treatment plans, and early detection of disease outbreaks [11]. Additionally, blockchain technology, known for its decentralized and tamper-resistant nature, can guarantee the security, privacy, and integrity of healthcare data, thereby, facilitating interoperability between different healthcare systems, providing seamless data sharing among various stakeholders while maintaining data privacy. The synergistic integration of AI, IoT, and blockchain in diagnosing pandemic diseases in smart cities holds immense potential for improving patient outcomes, enhancing public health management, and optimizing resource allocation. Jointly, these technologies can lead to quicker and more precise diagnoses, early intervention, and personalized treatment plans, leading to improved patient outcomes [12]. Moreover, the comprehensive health data collected by smart cities can provide valuable insights for public health management, enabling proactive measures to control disease outbreaks, optimize resource allocation, and design targeted interventions [10-12].

Despite the growing interest in the integration of AI, IoT, and blockchain for disease diagnosis in smart cities, there exists a research gap that needs to be addressed. While individual studies have explored the applications of AI, IoT, or blockchain in healthcare, there is a lack of comprehensive research focusing on the synergistic integration of these technologies specifically for disease diagnosis in smart cities. Limited studies have investigated the combined impact of AI's data analysis capabilities, IoT's real-time monitoring, and blockchain's secure data sharing in enhancing disease diagnosis in the unique context of smart cities. Additionally, there is a need for research that explores the challenges, feasibility, and potential risks associated with integrating these technologies. To this end, this paper will address the following specific research questions and hypotheses:

1) What are the key technical and operational challenges in integrating AI, IoT, and blockchain for disease diagnosis in the context of smart cities?
2) What are the potential benefits and opportunities of synergizing these technologies, such as enhanced accuracy, efficiency, and security?
3) What are the implications for patient outcomes, public health management, and resource allocation in leveraging this integration?
4) What is the data privacy, security, and ethical considerations associated with the combined use of AI, IoT, and blockchain in healthcare?
5) What are the recommended strategies, solutions, and regulatory frameworks to overcome challenges and maximize the opportunities of this integration?

Studying these research questions is expected to contribute to a comprehensive identification of the challenges and opportunities involved in synergizing AI, IoT, and blockchain for diagnosing pandemic diseases in smart cities. The primary objective of this paper is to explore the challenges and opportunities associated with the integration of AI, IoT, and blockchain for diagnosing Pandemic diseases in smart cities. The paper seeks to delve into the complexities surrounding data privacy, security, interoperability, and ethical considerations that arise in this integration process. Furthermore, it aims to highlight the opportunities presented by this convergence, such as improved accuracy, efficiency, and security in disease diagnosis.

The remaining part of this paper is structured as follows. Section 2 provides a concise background and review of the literature. Section 3 explores the control of Pandemic diseases in smart cities. Section 4 studies the convergence of the AI, IoT, and blockchain for Pandemic diseases in smart cities. Section 5 studies the main challenges and opportunities of the reviewed technologies. Section 6 concludes this study.

2. Background and Overview

The section provides a comprehensive overview of the key concepts, technologies, and existing research related to the integration of AI, IoT, and blockchain for diagnosing pandemic diseases in smart cities.

The research on smart cities developments involves leveraging cutting-edge technologies combined with data-driven insights for improving urban life positively. With the incorporation of IoT technologies, sensors, digital platforms along with various analytical tools have transformed how municipalities address challenges related to infrastructure modernization, delivery of public service availability while optimizing resources towards sustainable urban growth. In light of pandemic outbreaks globally across multiple regions maybe overcome with several advantages presented by smart cities [1-3]. AI algorithms promptly analyze health data such as symptoms, testing results, contact tracing information, enabling public health officials to identify community clusters at risk of becoming superspreaders. Digital platforms also present an opportunity for smart cities to disseminate actual information regarding pandemics like

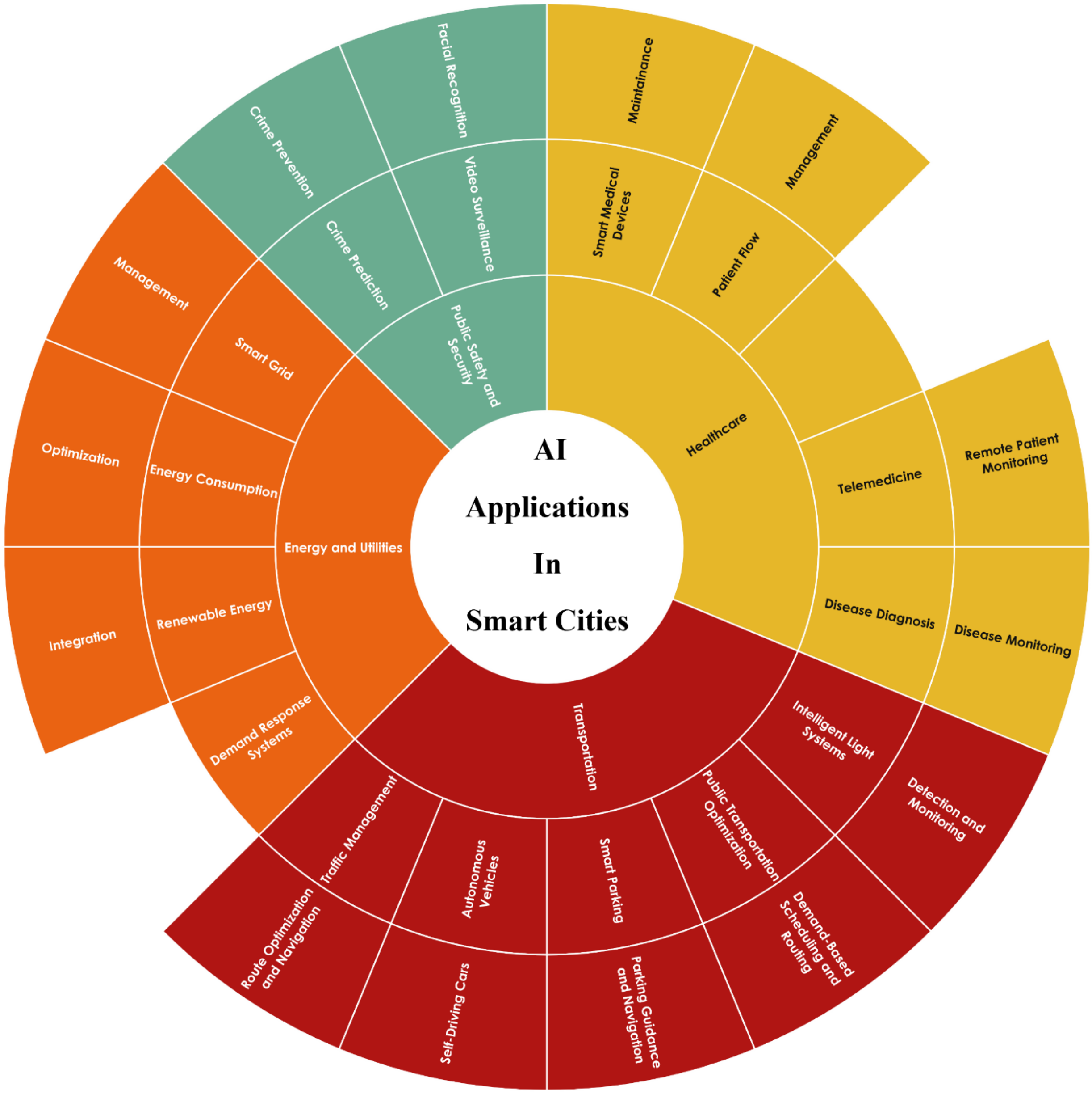

Figure 1. Visualization of our Taxonomy for categorizing AI applications in smart cities.

COVID-19 [5-6]. These platforms allow citizens to access real-time updates, interactive services such as remote healthcare support while promoting vaccination programs' equity and access [8-10].

2.1. AI in Smart Cities

AI has been playing a pivotal role in the development and optimization of smart cities, revolutionizing various aspects of urban life through empowering the smart cities to harness the power of data, automate procedures, and make knowledgeable decisions through analyzing vast volumes of data collected from sensors, IoT devices, and other sources [13-20]. This capability has been allowing smart cities to optimize resource allocation, improve efficiency in transportation systems, enhance public safety, and deliver personalized services to residents. AI has been empowering smart cities to address complex urban challenges by unlocking the potential of data-driven decision-making and enabling intelligent automation. In the context of smart cities, AI is extensively applied in transportation systems to optimize traffic flow, reduce congestion, and improve public transit efficiency. AI-powered algorithms could analyze real-time traffic data, identify patterns, and suggest ideal routes for vehicles, leading to reduced travel times and advanced road safety [20-30]. Moreover, AI has been used in smart parking systems to optimize parking space utilization and provide real-time information to drivers, minimizing the time and fuel wasted in searching for parking spots. The applications of AI solutions in smart technologies are numerous and span multiple areas, which can be summarized in our taxonomy presented in Figure 1. AI has a transformative impact on healthcare systems within smart cities, improving patient care, disease management, and public health outcomes. AI-powered healthcare solutions in smart cities leverage advanced algorithms to analyze large volumes of patient data, including medical records, diagnostic images, and genetic information. This enables healthcare providers to make accurate diagnoses, develop personalized treatment plans, and predict disease progression with greater precision [30-60]. AI algorithms are data driven by nature, hence identifying the publicly available datasets is significant to identify for researchers and practitioners. Taking the COVID-19 pandemic as an example, we provide a review of the relevant datasets for developing AI solutions In Table 1.

Table 1. Comparative review of literature datasets for developing AI solutions for COVID-19 screening.

References	Modality	Sample Size	# Class	#Patients	Country	Date	Data Format	Studies
[13]	X-ray	679	5	412	26 countries	2020	JPEG, PNG, JPG	[14-16]
[17]	X-ray	6286	3	NA	Italy, Spain, China	2020	/	[18-20]
[21]	X-ray	452	3	NA	Canada	2020	JPG, PNG	[22-24]
[25]	X-ray	21,295	3	NA	/	2020	JPG	[26-27]
[28]	X-ray	852	3	NA	Spain	2020	JPG	[29-30]
[31]	X-ray	1559	3	NA	China	2022	JPG	[32]
[33]	X-ray	4703	3	NA	Italy	2020	DICOM	[34-35]
[36]	X-ray	30,000	3	16	Canada	2021	PNG	[37-38]
[39]	CT	812	2	NA	China	2020	PNG, JPG	[40-41]
[43]	CT	617,775	2	NA	China	2020	JPG, PNG	[44-45]
[46]	CT	20	2	NA	China	2020	DICOM	[16]
[47]	CT	165,667	2	861	China	2020	/	[28], [40]
[48]	CT	20,685	3	1521	Russia	2020	NIFIT	[42]
[49]	CT	2482	2		Brazil	2020	PNG	[43]
[50]	CT	340190	3		China	2020	PNG	[45]
[51]	CT	19685	3	1521	China	2020	DICOM, JPEG	[36]
[52]	CT	2724	2	2617	China, Japan, Italy	2020	/	[38]
[53]	CT	34,006	3	NA	China	2020	JPG	[12]
[54]	CT	145,167	3	NA	China	2021	JPG	[22]
[55]	CT	63,849	2	235	Iran	2021	TIFF	[16]
[56]	CT	308	3	305	Iran	2021	DICOM	[25]
[57]	CT	1566	3	201	Turkey	2022	JPG	[38]

[58]	CT	376,000	3	1000+	/	2022	JPG	[40]
[59]	X-ray / CT	18840/6687	COVID/No/Others	1,311	Spain	2020	/	[45]
[60]	X-ray / CT	1327/263	3	NA	USA	2020	/	[11]

2.2. IoT in Smart Cities

Cities that leverage the IoT as part of its infrastructure offer citizens improved quality of life. Real-time data collected from various interconnected devices within these cities including sensors helps gain insights into different elements such as environmental factors or energy consumption patterns. Efficient communication within this network leads to informed decision-making and well-planned operational adjustments across various sectors towards optimized service delivery. Smart cities equip central infrastructure with dynamic sensing devices programmed to detect and track changes intended for efficient resource planning and allocation. Connected vehicles' smart traffic signals installed along main transportation routes generate on-the-spot route diversions, easing stressors related to road congestion. Moreover, digital solutions-driven waste management optimization tools explore fleet tracking systems that incorporate real-time bin-fill level sensing equipment leading to reduced trash collection costs due to effective curbside waste distribution strategies [61-65]. In essence, this technology supports urban sustainability strategies by providing valuable insights crucial for better urban planning - in real-time. IoT has a substantial influence on health monitoring, and emergency response within smart cities (See Figure 2). IoT devices, such as surveillance cameras, environmental sensors, and wearable health trackers, provide real-time data on public spaces, air quality, and individual health parameters. This information enables early detection of safety hazards, pollution levels, and disease outbreaks, facilitating prompt interventions and preventive measures. For instance, IoT-based emergency response systems can automatically detect and report incidents such as fires or accidents, enabling faster emergency services and improving overall public safety. IoT-powered health monitoring devices allow continuous remote monitoring of patients, enabling timely interventions, and reducing the need for hospital visits [66-70].

Several literature studies have been performed to explore and survey the application of IoT in smart cities [61-75]. A comprehensive review and comparison of these studies reveal key insights into the diverse domains where IoT is

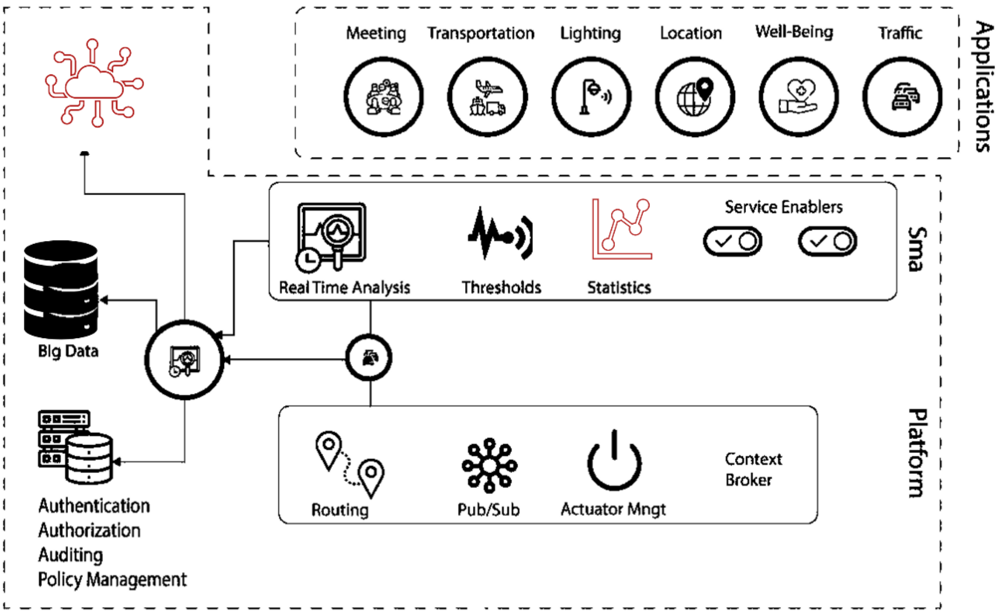

Figure 2. Illustration of the general workflow of the IoT applications in smart cities.

employed. Table 2 presents an overview of cutting-edge literature studies, emphasizing their research focus, methodology, key findings, limitations, contributions, etc. Through different research approaches, these studies have demonstrated the potential of IoT in optimizing resource consumption, improving infrastructure efficiency, enhancing healthcare services, and ensuring public safety.

Table 2. Comparative review of literature surveys on the role of AI in smart cities.

Study	Objective	Methodology	Key Findings	Application Area	IoT Technologies	Challenges Addressed	Limitations	Future Directions
[61]	Investigate fog computing approaches in IoT-enabled smart cities	Literature review and case study analysis	- Enhanced scalability and resource efficiency through fog computing	Smart cities	Fog computing, IoT platforms	Scalability, resource allocation, latency	Limited case studies available, diverse.	Optimization of fog node placement
[62]	Conduct a systematic review on semantic interoperability in IoE-enabled smart cities	Systematic literature review	- Improved data exchange and integration among heterogeneous IoT devices	Smart cities	Semantic interoperability frameworks, IoT protocols	Data integration, semantic mapping,	Limited standardization across domains, complexity	Semantic interoperability frameworks, standardization of IoT models
[63]	Survey the landscape of explainable AI (XAI) for smart cities	Survey and literature review	- Increased transparency and interpretability of AI algorithms in smart city applications	Smart cities	Machine learning algorithms, XAI techniques	Interpretability, explainability, accountability	Diversity of AI techniques, complexity of urban data	Development of XAI frameworks for urban applications
[64]	Review the digital twin technology in smart grid, transportation system, and smart city	Literature review and case study analysis	- Improved system monitoring and control through virtual replicas of physical assets	Smart grid, transportation, smart cities	Digital twin platforms, simulation models	System modeling, real-time data integration, data privacy	Limited implementation cases, scalability challenges	Enhanced simulation capabilities
[65]	Discuss recent advances, taxonomy, and open research challenges in urban computing for sustainable smart cities	Literature review and analysis	- Improved understanding and utilization of urban data	Sustainable smart cities	Data analytics, machine learning, urban computing frameworks	Data quality, scalability, privacy	Lack of unified frameworks, data heterogeneity	Development of intelligent urban systems
[66]	Investigate the collection, processing, and secondary use of personal and anonymized data in smart cities	Case study analysis and survey	- Facilitated collection and analysis of personal and anonymized data	Smart cities	Data processing platforms, anonymization methods	Data privacy, consent management, data governance	Ethical considerations, data anonymization accuracy	Dynamic consent frameworks
[67]	Conduct a systematic review of the effective use of smart cities in crisis cases	Systematic literature review	- Enhanced emergency response and crisis management	Crisis management, smart cities	IoT sensors, communication networks, emergency response systems	Crisis preparedness, real-time data integration, citizen engagement	Limited case studies available, heterogeneous crisis scenarios	Integration of AI and predictive analytics
[68]	Provide an overview of cyber threats, attacks, and countermeasures on the primary domains of smart cities	Literature review and analysis	- Increased understanding of cyber threats and vulnerabilities in smart city domains	Smart cities	Encryption, intrusion detection systems, access control mechanisms	Cyber threats, vulnerability assessment, incident response	Rapidly evolving cyber threats, resource constraints	Development of threat intelligence platforms
[69]	Review concepts, frameworks, and key technologies for IoT-enabled smart cities	Literature review and analysis	- Improved understanding of IoT-enabled smart city concepts and architectures	IoT-enabled smart cities	IoT protocols, cloud platforms, data analytics tools	Scalability, interoperability, data privacy	Lack of standardized frameworks, technology integration challenges	Development of holistic smart city frameworks, interoperability standards
[70]	Investigate fog computing approaches in IoT-enabled smart cities	Literature review and case study analysis	- Enhanced scalability and resource efficiency through fog computing	Smart cities	Fog computing, IoT platforms	Scalability, resource allocation, latency	Limited case studies available, diverse implementation approaches	optimization of fog node placement
[71]	Map optimization problems for IoT-enabled smart city development, including applications, objectives, and constraints	Literature review and analysis	- Identified optimization problems and their applications in IoT-enabled smart cities	IoT-enabled smart cities	Mathematical optimization, IoT sensors, decision support systems	Resource allocation, multi-objective optimization, scalability	Limited case studies, complex decision-making scenarios	dynamic resource allocation models
[72]	Provide a contemporary survey on IoT-based smart	Literature review and analysis	- Explored IoT-based smart city	IoT-based	IoT protocols, cloud	Interoperability, security, data privacy	Lack of standardized architectures,	privacy-enhancing technologies

	cities, including architecture, applications, and open issues		architectures and their components	smart cities	platforms, data analytics tools		technology integration challenges	
[73]	Review the IoT and smart city domains, identifying existing knowledge and research gaps	Systematic literature review	- Established an overview of IoT and smart city concepts, frameworks, and technologies	IoT, smart cities	IoT protocols, cloud platforms, data analytics tools	Standardization, governance, sustainability	Fragmented research landscape, lack of comprehensive frameworks	Development of unified IoT frameworks
[74]	Discuss cybersecurity challenges of IoT-enabled smart cities through a survey of existing literature	Literature review and survey	- Identified cybersecurity threats and challenges specific to IoT-enabled smart cities	IoT-enabled smart cities	Encryption, intrusion detection systems, access control mechanisms	Cyber threats, vulnerability assessment, incident response	Rapidly evolving cyber threats, resource constraints	Development of threat intelligence platforms
[75]	Review smart city dimensions and associated risks through a literature review	Literature review and analysis	- Identified key dimensions and components of smart cities	Smart cities	Data governance, privacy regulations, risk assessment frameworks	Data privacy, cybersecurity, governance	Lack of standardized risk management frameworks, diverse risk profiles	proactive risk mitigation strategies

2.3. Blockchain in Smart Cities

Blockchain technology is gaining substantial recognition as a highly versatile platform capable of delivering multiple applications beyond its initial use case for cryptocurrencies such as Bitcoin. In smart city operations, Blockchain enables a transparently distributed platform that performs secure validation and recording of transactions, data exchanges & individuals' digital identities' verification [76-78]. It serves as an unalterable decentralised ledger that interconnects blocks giving unparalleled assurances in information transactional history & actuality. Data security issues continue to pose significant challenges to prevent data breaches in complex urban environments with multiple stakeholders requiring access to varying types of sensitive information e.g., Government agencies and citizens with keen interest in accessing their personal energy consumption records amongst countless others — however, using validation through blockchain offers unique protection protocols by preventing unauthorized modification or unwarranted access attempts on restricted pieces of data in daunting smart city environments [79-80]. Efficient and automated management structures are crucial for ease-of-use during day-to-day operations; smart contracts executed on a decentralized blockchain platform eliminate intermediaries involved reducing storage overhead costs while streamlining processes like property trading or supply chain management. Providing transparency supporting accountability and traceability through an immutable decentralized ledger could also facilitate efficient public delivery mechanisms, such as welfare distribution or infrastructure maintenance programs at cost-effectiveness levels that foster stakeholder commitments in governance efforts. Blockchain technology further presents self-sovereign identity systems empowering individuals to manage their digital identities rigorously while providing selective control over the sharing of their personal information, thus ensuring citizens' protection from unscrupulous third parties accessing sensitive data aspects for undesired intentions [81-83].

Blockchain technology has gained significant attention because of its prospective applications in various sectors of smart cities and pandemic control systems. Different types of blockchain can be employed in these contexts, each offering unique features and functionalities. Table 3 presents a comprehensive comparison of the most used blockchain types, highlighting their characteristics, advantages, and limitations. Firstly, public blockchains, such as Bitcoin and Ethereum, are decentralized networks open to all participants, offering transparency and immutability. However, they suffer from scalability issues and limited privacy [80-83]. On the other hand, private blockchains, such as Hyperledger Fabric and Corda, are permissioned networks where access and participation are restricted to authorized entities, guaranteeing higher privacy and performance. Hybrid blockchains, like Quorum and Dragonchain, merge elements of both public and private blockchains, allowing for customizable levels of transparency and privacy.

Moreover, consortium blockchains, such as Ripple and MultiChain, are governed by a consortium of organizations, enabling collaborative efforts while maintaining control over the network [82-85].

Table 3. Comparison between different types of blockchain.

Blockchain Type	Use Cases	Advantages	Challenges	Scalability	Privacy	Governance
Public Blockchain	Health data exchange, clinical trials, patient consent management	Transparency, immutability, interoperability	Scalability, energy consumption, privacy concerns	Varies (e.g., Ethereum's PoS transition, Layer 2 solutions)	Varies (e.g., pseudonymity, data privacy concerns)	Decentralized governance, community-driven decision-making
Private Blockchain	Electronic health records, supply chain integrity, healthcare provider credentialing	Efficiency, privacy, control	Centralization, limited network size, trust among participants	Scalable within the defined network	Enhanced privacy controls, restricted access	Centralized governance, trusted authorities
Consortium Blockchain	Health information sharing networks, patient data interoperability, research collaborations	Shared control, increased efficiency, scalability	Governance structure, consensus mechanisms, interoperability	Scalable within the consortium	Configurable privacy settings, controlled access	Consortium-based governance, shared decision-making
Hybrid Blockchain	Interoperable health data exchange, secure telemedicine, consent-based data sharing	Customizable access control, scalability options	Complexity, interoperability challenges, potential centralization	Scalable within the defined network	Configurable privacy settings, controlled access	Varies (can be consortium-based or custom governance)

3. Sustainable Pandemic Control in Smart Cities

In recent years, smart cities have arisen as a favorable solution for addressing several urban challenges, including the management of pandemic outbreaks. The incorporation of advanced technologies such as AI, IoT, and blockchain has provided new opportunities for effective and sustainable pandemic control in urban environments. In this section, we delve into the theory of sustainable pandemic control in smart cities, concentrating on the application of these technologies to improve disease surveillance, early detection, and response mechanisms (see Figure 3).

3.1. Early Detection and Surveillance

Urban areas can strategically place these sensors around the city- capturing critical insights such as pollution levels impacting respiratory illnesses or environmental factors that influence common disease transmissions [86]. Furthermore, wearable gadgets or other mobility applications gather real-time health data from individuals through vital sign measurements- automatic symptom reporting along with their recent travel history- providing an essential perspective for disease surveillance efforts. Urban centers that use AI algorithms integrated with all this insightful information gathered from multiple sources at scale could identify hotspot regions where determined anomalies might indicate emerging disease outbreaks rapidly vs., traditional methods relying retrospectively on human-reported incidents alone [87]. Through real-time monitoring of IoT devices and sensors in smart cities, authorities can act swiftly when responding to disease outbreaks. To achieve this, cities must establish platforms for integrated data fusion and

Figure 3. operational framework for sustainable pandemic control in smart cities

advanced analytics that support coordination across various sources such as healthcare records, social media insights, and environmental sensor observations [88]. Using social media discussions alongside other sources helps identify potential indicators or geographical locations poised for an outbreak before it occurs. Fortified with such information allows governments launch targeted interventions like increased testing or awareness campaigns aimed at combating infections effectively [89].

Several smart cities around the world have implemented proactive surveillance systems to monitor the spread of pandemics and take timely preventive actions. For instance, Singapore's smart city initiatives have demonstrated remarkable success in leveraging technology for pandemic control [90]. Through their "TraceTogether" program, Singapore implemented a contact tracing system that utilizes Bluetooth technology to identify and notify individuals who have been near COVID-19 cases. This real-time data enables quick identification and isolation of potentially infected individuals, helping to contain the spread of the virus. Additionally, South Korea's smart city efforts have been highly effective in monitoring and managing the COVID-19 outbreak [86-89]. The country established an extensive testing and surveillance system that integrates data from various sources, including healthcare records, mobile phone tracking, and credit card transactions. This integrated approach allows for efficient contact tracing and early detection of outbreaks, enabling swift responses, targeted interventions, and effective containment measures. These examples highlight how proactive surveillance systems in smart cities can play a crucial role in monitoring and managing the spread of pandemics, ultimately helping to safeguard public health and minimize the impact of infectious diseases [90].

3.2. Contact Tracing and Monitoring

Contact tracing and monitoring have become essential components of pandemic control within smart cities, with digital technologies playing a significant role in these efforts. Mobile applications and wearables have emerged as powerful tools for contact tracing and monitoring the movement of individuals. Through mobile applications, individuals can voluntarily report their symptoms, undergo self-assessment, and receive real-time alerts and updates related to COVID-19 [91]. These applications utilize Bluetooth technology to record proximity data between devices, enabling the identification of close contacts in case of a confirmed infection. Wearable devices, such as smartwatches or fitness trackers, can also contribute to contact tracing by capturing data on individuals' proximity, movement patterns, and vital signs. This information allows for timely testing, contact notifications, and appropriate quarantine measures, minimizing the spread of the virus within the community. The use of digital technologies for contact tracing and monitoring empowers individuals to take proactive measures, helps authorities make informed decisions, and plays a crucial role in curbing the transmission of infectious diseases in smart cities [92].

Self-isolation is a energetic approach in containing the spread of infectious diseases, and IoT devices joint with AI algorithms can play a significant role in identifying potential high-risk contacts and alerting individuals for testing or self-isolation within smart cities. IoT devices, such as wearable devices and smart home sensors, can track proximity data and movement patterns of individuals [93]. Once potential high-risk contacts are identified, automated alerts can be sent to individuals, notifying them of their potential exposure and providing guidance on self-isolation and testing. This technology enables a more targeted and efficient approach to self-isolation, allowing resources and public health efforts to be focused on individuals who are at higher risk of spreading the disease. During the COVID-19 pandemic, numerous examples have demonstrated the effectiveness of IoT devices and AI algorithms in supporting self-isolation measures. In countries like South Korea and Taiwan, individuals under quarantine were required to wear electronic wristbands or use mobile applications that monitored their location and ensured compliance with self-isolation measures. If an individual violated the quarantine rules or moved outside the designated area, an alert would be triggered, prompting authorities to take appropriate action [94]. This approach aided to enforce self-isolation effectively and minimize the risk of disease communication. Such examples highlight the potential of IoT devices and AI algorithms to support self-isolation efforts, improve compliance, and ultimately contribute to the control and containment of infectious diseases in smart cities [91-95].

3.3. Data-Driven Decision Making

Smart cities can leverage data analytics and AI algorithms to inform decision-making processes during a pandemic, enabling more effective and evidence-based strategies [96]. AI algorithms can process this data to identify trends, detect potential outbreaks, and predict the spread of infectious diseases. For instance, machine learning algorithms can analyze real-time data on COVID-19 cases, hospital admissions, and healthcare capacity to provide accurate forecasts of future demand, aiding decision-makers in planning and allocating resources effectively [97]. Data analytics can also contribute to understanding population mobility patterns, identifying high-risk areas, and designing targeted interventions to limit the transmission of the disease. The COVID-19 pandemic has demonstrated the value of data analytics and AI algorithms in informing decision-making within smart cities [98]. A notable example is the city of Seoul in South Korea, which effectively employed data analytics and AI technologies to manage the outbreak. Seoul's Metropolitan Government utilized a comprehensive data platform that integrated information from various sources, including health records, immigration data, credit card transactions, and mobile phone location data [99]. This data-driven approach played a vital role in Seoul's successful response to the pandemic, enabling the city to implement targeted testing and isolation measures, effectively manage healthcare capacity, and minimize the impact on public health. The example of Seoul highlights how smart cities can harness the power of data analytics and AI algorithms to make informed decisions and navigate the complexities of a pandemic effectively [100].

The integration of diverse data sources, such as healthcare data, mobility patterns, and socioeconomic factors, is crucial in predicting disease spread and planning resource allocation within smart cities. Healthcare data, including information on COVID-19 cases, hospitalizations, and testing results, provides valuable insights into the prevalence and severity of the disease [96]. Mobility patterns, derived from sources like transportation data and mobile phone tracking, offer crucial information on population movement, identifying potential transmission routes and areas of high risk. Socioeconomic factors, such as population density, income levels, and access to healthcare, contribute to the understanding of disparities and vulnerabilities in different communities. This integration conceptually allows proactive decision-making, resource optimization, and targeted interventions, ultimately improving the effectiveness of disease control measures within smart cities [98-99]. The COVID-19 pandemic has practically demonstrated the implication of mixing diverse data sources in predicting disease spread and apportioning resources effectively. An example can be seen in the city of New York, which faced significant challenges during the outbreak. To address this, the city leveraged diverse data sources to inform its response. They also analyzed mobility data to monitor population movement, identify potential hotspots, and enforce targeted containment measures. Moreover, socioeconomic factors, such as poverty rates and access to healthcare, were considered to address disparities in healthcare outcomes and ensure equitable distribution of resources. The incorporation of these diverse data sources played a critical role in New York City's response to the pandemic, helping to control the spread of the virus, allocate resources effectively, and mitigate the impact on public health. This example exemplifies the power of integrating multiple technologies in smart cities, emphasizing the importance of leveraging diverse data sources to predict disease spread and plan resource allocation during a pandemic [100].

3.4. Remote Healthcare and Telemedicine

Smart cities can leverage telemedicine and remote healthcare technologies to ensure continuous access to healthcare services during a pandemic. Telemedicine enables individuals to receive medical consultations, monitoring, and follow-up care remotely, reducing the need for in-person visits and minimizing the risk of disease transmission [101]. Through video conferencing, online platforms, and mobile applications, healthcare providers can remotely diagnose and treat patients, offer medical advice, and monitor their health conditions. Remote healthcare technologies, such as wearable devices and home monitoring systems, enable the collection of vital signs and health data from patients at their homes, facilitating remote patient monitoring and early detection of potential complications [102]. This approach not only ensures the continuity of healthcare services during a pandemic but also reduces the burden on healthcare facilities, optimizes resource allocation, and enhances the overall efficiency and effectiveness of healthcare delivery within smart cities. The use of IoT-enabled medical devices for remote patient monitoring holds immense potential in smart cities, particularly during a pandemic. These devices, such as wearable sensors, smart patches, and connected medical devices, enable healthcare providers to remotely monitor patients' vital signs, collect real-time health data, and deliver timely interventions [103]. This remote monitoring capability allows for early detection of any concerning trends or abnormalities, enabling healthcare providers to intervene promptly and provide appropriate care. IoT-enabled medical devices facilitate personalized and proactive healthcare, as patients can receive remote monitoring and interventions tailored to their specific needs and conditions [104]. The COVID-19 pandemic has witnessed a surge in the adoption of telemedicine and remote healthcare technologies as a means to maintain access to healthcare services. An example can be seen in the United States, where healthcare systems rapidly expanded telehealth services to ensure continued patient care while reducing the risk of viral transmission. Many healthcare providers started offering virtual consultations, enabling patients to receive medical advice, prescriptions, and follow-up care remotely. Additionally, remote monitoring technologies played a crucial role in monitoring the health status of COVID-19 patients in home quarantine. Through the use of wearable devices and remote monitoring platforms, healthcare professionals were able to remotely monitor patients' vital signs, oxygen levels, and symptoms, providing timely interventions and minimizing the need for hospitalizations. This example highlights how smart cities can leverage telemedicine and remote healthcare technologies to overcome geographical barriers, ensure continuous access to healthcare services, and support effective disease management during a pandemic [101-104]. Virtual consultations and digital health platforms have emerged as valuable tools in reducing the burden on healthcare facilities and minimizing the risk of disease transmission within smart cities. Virtual consultations enable healthcare providers to connect with patients remotely through video conferencing or telecommunication platforms [105]. This allows individuals to seek medical advice, receive diagnoses, and discuss treatment options from the comfort of their homes. Additionally, virtual consultations offer convenience and accessibility, particularly for individuals with limited mobility or those residing in remote areas. Patients can access quality healthcare services without the need for long-distance travel or waiting in crowded healthcare settings. This not only reduces the burden on healthcare facilities but also improves patient satisfaction and engagement in their own healthcare management [106-107].

3.5. Public Communication and Education

Effective communication strategies play a vital role in smart cities to disseminate accurate information, guidelines, and updates during a pandemic. Clear and timely communication is critical to guarantee that inhabitants, healthcare professionals, and other stakeholders have access to reliable information regarding the virus, preventive measures, testing protocols, treatment options, and vaccination campaigns. Accurate and reliable information serves as a powerful tool in combating misinformation, rumors, and panic within smart cities. Through various communication channels, such as official websites, social media platforms, mobile applications, and public announcements, smart cities can provide up-to-date information from reputable sources, such as healthcare authorities and government agencies [108]. This information can include guidelines for physical distancing, hygiene practices, mask-wearing, and quarantine measures. Moreover, effective communication strategies enable the dissemination of critical updates on the developing situation, such as new variants, testing availability, vaccine distribution plans, and changes in public health policies. Communication platforms can also provide channels for individuals to ask questions, seek clarifications, and share concerns, allowing authorities to address misconceptions, provide support, and build a stronger sense of community resilience [109]. Additionally, communication strategies can be tailored to reach diverse populations, considering language barriers, cultural sensitivities, and accessibility needs. This comprehensive approach ensures that accurate information reaches all segments of the population, reducing disparities in healthcare access and promoting equitable public health outcomes. During the COVID-19 pandemic, effective communication policies have played a pivotal role in smart cities worldwide. Examples include the establishment of dedicated hotlines and helplines to address public inquiries, the use of social media campaigns to promote accurate information and debunk myths, and the deployment of mobile applications to deliver real-time updates and notifications [110]. These strategies have enabled authorities to swiftly communicate changes in guidelines, alert individuals to potential exposure risks, and inform residents about testing centers, vaccination sites, and healthcare resources. The COVID-19 pandemic has highlighted the reputation of operative communication in smart cities, highlighting the need for clear, consistent, and accessible messaging to ensure a well-informed and engaged community response. AI-powered chatbots have arose as valuable tools for smart cities in providing personalized and instant responses to citizens' queries. These chatbots, integrated into digital platforms and social media channels, leverage natural language processing and machine learning algorithms to comprehend and reply to users' questions precisely. They can deliver real-time information on symptoms, testing centers, safety precautions, and other relevant topics. AI-powered chatbots not only assist in handling a high volume of inquiries professionally but also proposal a reliable and standardized approach to information dissemination. Citizens can accept rapid responses to their queries, enhancing their trust in the information provided and reducing the burden on human resources [111].

Several smart cities around the world have successfully implemented robust communication strategies to promote public awareness, adherence to preventive measures, and vaccination campaigns during the COVID-19 pandemic.

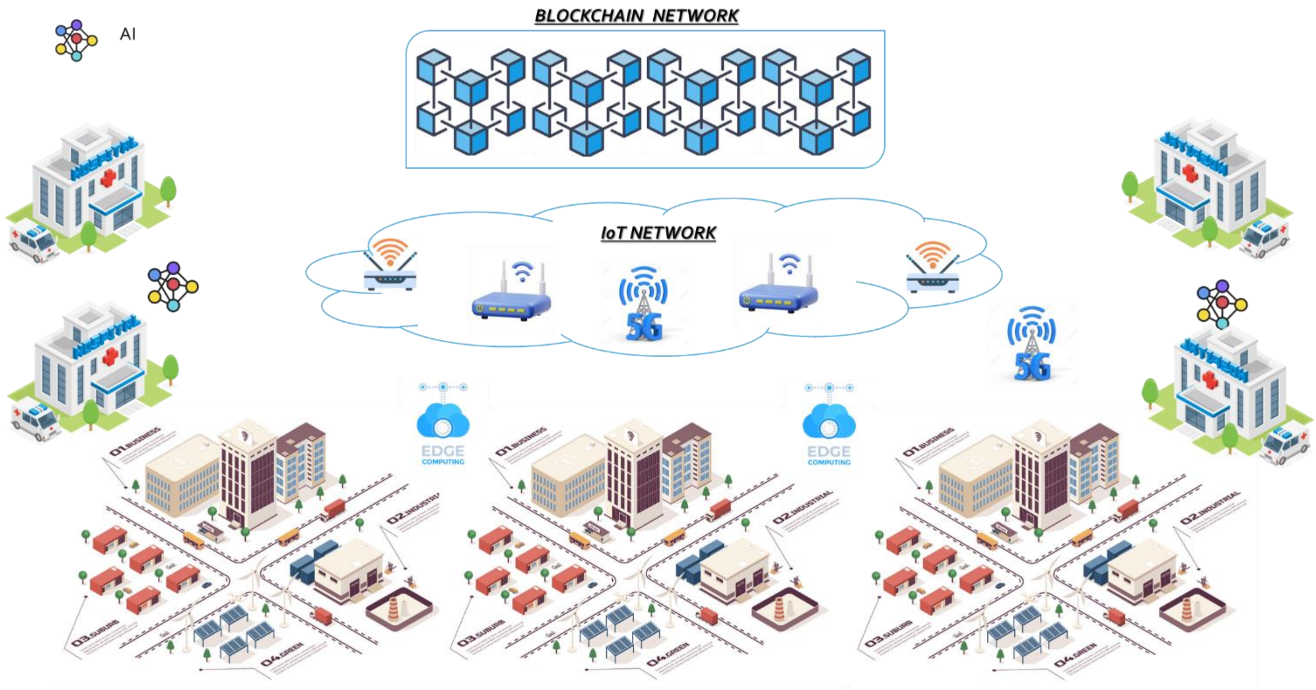

Figure 4. Integration of AI, IoT, and Blockchain for pandemic control in smart cities.

These cities have demonstrated exemplary efforts in leveraging technology and effective messaging to engage their communities and ensure a coordinated response to the crisis. One such example is Singapore, where the government utilized various communication channels, including social media, mobile applications, and public announcements, to disseminate accurate information, guidelines, and updates [100]. Through their "SG Clean" campaign, Singapore emphasized the importance of personal hygiene, cleanliness, and safe distancing measures, encouraging residents to adopt these practices and contribute to the collective effort in controlling the spread of the virus. Another successful example is Seoul, South Korea, which utilized a comprehensive communication strategy to raise public awareness and facilitate effective contact tracing. The city implemented a mobile application called "Smart Seoul Map" that provided real-time information on COVID-19 cases, testing locations, and quarantine measures. The application enabled citizens to access accurate information, report symptoms, and seek testing if necessary [105-110]. Furthermore, Seoul established a 24/7 COVID-19 hotline to address citizens' queries, provide guidance, and offer psychological support. These initiatives helped in building trust, reducing anxiety, and fostering community engagement in adhering to preventive measures and contact tracing efforts. Moreover, Barcelona, Spain, implemented an innovative communication strategy during the pandemic. The city launched a digital platform called "Barcelona Health Hub" to provide citizens with access to reliable information, telehealth services, and mental health support. The platform facilitated virtual consultations, enabling individuals to consult with healthcare professionals remotely. Barcelona also utilized social media campaigns and targeted messaging to promote adherence to preventive measures and vaccination campaigns [111]. These initiatives contributed to the effective dissemination of information, enhanced public awareness, and facilitated remote access to healthcare services. These successful examples demonstrate the importance of robust communication strategies in smart cities during a pandemic [109]. The implementation of such strategies has not only contributed to controlling the spread of the virus but also fostered a sense of unity, trust, and resilience among citizens. These examples serve as valuable lessons for other smart cities seeking to implement effective communication strategies to combat infectious diseases and promote public health [110].

4. Synergies AI, IoT, and Blockchain for pandemic control

In designing pandemic control systems for smart cities (See Figure 4), the role of IoT is instrumental. IoT devices, equipped with sensors and connectivity capabilities, allow the collection and transmission of real-time data from various sources, including environmental sensors, wearables, and healthcare devices. This vast network of interconnected devices procedures the foundation for building a comprehensive and proactive pandemic control system. One key facet of IoT in pandemic control is the capability to monitor and track the movement of individuals within smart cities [65]. This information can be leveraged to perceive potential hotspots, identify high-risk areas, and implement targeted interventions to mitigate the spread of infectious diseases. Furthermore, IoT-based contact tracing solutions, utilizing Bluetooth technology or other proximity sensing mechanisms, can offer valuable insights into the interactions and potential exposures of individuals, enabling rapid notification and preventive measures [67]. Moreover, IoT plays a vital role in attractive the situational awareness and response capabilities of pandemic control systems. Through the integration of IoT devices with surveillance cameras, drones, and other monitoring technologies, real-time data on crowd movements, mask compliance, and hygiene practices can be captured. For instance, IoT data can facilitate the efficient deployment of healthcare resources to areas experiencing a surge in cases, enable predictive modeling for effective planning, and support the implementation of dynamic control measures based on the real-time status of the pandemic [72].

Further edge computing, fog computing, and cloud computing play crucial roles in enabling efficient and effective data processing, analysis, and decision-making in the design of pandemic control systems. Each of these computing paradigms offers unique capabilities and benefits that contribute to the overall architecture and functionality of the pandemic control system in a smart city [77]. Edge computing, as its name advocates, emphases on processing data at the edge of the network, closer to the data source. In our case, edge computing enables real-time data processing and analysis at the device or sensor level. At the edge side, AI algorithms can be deployed on edge devices to enable real-time data processing, analysis, and decision-making [81]. These devices can collect and process data from various sensors and devices, such as wearables or temperature scanners, to detect potential COVID-19 cases or monitor social distancing compliance. AI models running on the edge can provide immediate insights and alerts, reducing the latency and bandwidth requirements for transmitting data to centralized systems. This allows for quicker response times and more efficient local interventions, enhancing the effectiveness of pandemic control measures in smart cities [82].

Fog computing builds upon the thought of edge computing and spreads it to a broader scale. It includes the deployment of fog nodes or mini data centers at intermediate points within the network infrastructure, such as access points or base stations. These fog nodes aid as middle processing hubs between the edge devices and the cloud. In our case, fog computing can enable localized data aggregation, analysis, and decision-making [84].

Cloud computing, on the other hand, offers the scalability, storage capacity, and computational resources needed for handling large-scale data processing and complex analytics. In pandemic control systems, cloud computing serves as the central repository for storing and analyzing aggregated data from various sources. It enables unconventional data analytics, AI algorithms, and predictive modeling to generate actionable insights for decision-makers. Cloud computing also facilitates the integration of diverse data sources, such as healthcare records, environmental data, and social media feeds, enabling a holistic interpretation of the pandemic situation. In addition, cloud-based solutions support cooperative labors among diverse stakeholders by providing a centralized platform for data sharing, resource coordination, and decision coordination [100].

In designing pandemic control systems for smart cities, the convergence of blockchain with edge computing, fog computing, and cloud computing presents promising in enhancing data integrity, transparency, and security, while the computing paradigms provide the essential computational power and infrastructure to support blockchain-based solutions. At the edge side, blockchain can be used to establish trust and secure data exchange among edge devices in the pandemic control system [99]. Blockchain can also ease secure and privacy-preserving communication protocols among edge devices, enhancing the overall security of the system. Moreover, the use of blockchain in edge computing can enable decentralized decision-making and coordination among edge devices, ensuring the reliability and resilience of the pandemic control system. Likewise, in fog computing, blockchain can play a decisive role in founding trust and enabling secure communication among fog nodes [55]. Through applying blockchain's consensus mechanisms, fog nodes can sustain a shared and distributed ledger of transactions, guaranteeing the integrity and transparency of data exchanges. Blockchain can permit secure data aggregation and processing across fog nodes, allowing for efficient and reliable analysis of pandemic-related data. Moreover, blockchain-based smart contracts can industrialize the execution of agreements and coordination among fog nodes, enhancing the efficiency and trustworthiness of the pandemic control system in fog computing environments.

In cloud side, the convergence with blockchain provides opportunities for secure and transparent data storage, sharing, and analysis. Blockchain technology can be adopted to generate an auditable and immutable record of data transactions and access permissions in the cloud. This guarantees data integrity and provides a transparent view of how data is managed and utilized within the pandemic control system. Blockchain can also enhance the security of cloud-based solutions by mitigating the risks of unauthorized access or tampering. Smart contracts deployed on the blockchain can automate and enforce data privacy policies, ensuring that sensitive data is handled in a compliant and secure manner. Furthermore, blockchain-based frameworks can enable data provenance and consent management, empowering individuals to have more control over their personal health data in the cloud. In the cloud side, AI plays a crucial role in large-scale data analysis, modeling, and prediction. Cloud-based AI systems can aggregate and analyze data from multiple sources, such as healthcare records, mobility patterns, and social media, to gain a comprehensive understanding of the pandemic's dynamics. AI models trained on this data can provide insights into disease transmission patterns, vulnerable populations, and the effectiveness of control measures. Cloud-based AI systems can also support resource optimization and healthcare planning by forecasting hospitalizations, ICU bed utilization, and vaccine distribution.

In the blockchain side, AI can be used to enhance the capabilities of blockchain-based pandemic control systems. AI algorithms can analyze blockchain data to identify patterns, anomalies, and insights that can contribute to disease surveillance, contact tracing, and early warning systems [83]. AI can also support the development of AI-powered smart contracts that automate compliance with health protocols, enforce data privacy policies, and ensure secure and transparent data sharing within the blockchain network. Furthermore, AI techniques such as natural language processing and sentiment analysis can be applied to blockchain data to monitor public sentiment, identify misinformation, and facilitate effective communication strategies during a pandemic. The combination of AI and blockchain in pandemic control systems can enhance transparency, trust, and the overall effectiveness of smart city initiatives [85-88].

5. Challenges and Opportunities

In this section, we dive into the details of the intrinsic challenges and open issues evolving from integration of AI, IoT, and blockchain into healthcare sector to empower intelligent and automatic diagnosis of pandemic diseases within smart cities. While the hypothetical advantages of this synergy are significant, it is decisive to address the various obstacles that can thwart its effective and sustainable implementation. Through a comprehensive investigation of these challenges (see Table 4), we can gain a deeper understanding of the deliberations required for successful integration of the surveyed technologies to pave the way for future advancements in the healthcare sector of smart city.

Table 4. Summary of the popular research challenges facing the integration of AI, IoT, and Blockchain for pandemic control in smart cities.

Challenge	Sub-challenge	Main Reasons	Impact on Pandemic Control	Possible Solutions	Criticality	Feasibility	Cost
Interoperability and Standardization	Integration complexity	Diverse data formats and protocols	Hinders seamless data exchange and collaboration	Establish data interoperability standards	High	Med	High
	Lack of standardized interfaces	Incompatible systems and devices	Impedes integration and data sharing capabilities	Develop and enforce standardized interfaces	High	Med	Med
	Lack of interoperable AI models	Inefficient model sharing and collaboration	Limits scalability and effectiveness of AI applications	Develop standardized AI model frameworks	Med	High	High
Data Privacy and Security	Consent management and control	Lack of transparency and individual control	Erodes trust and privacy rights of individuals	Implement robust consent and control mechanisms	High	High	Med
	Unauthorized access and data breaches	Vulnerabilities in systems and networks	Jeopardizes confidentiality and integrity of personal health data	Implement strong security measures	High	High	High
	Secondary use and re-identification risks	Improper handling and de-identification methods	Raises privacy concerns and potential harm to individuals' privacy	Implement proper de-identification techniques	Med	Med	Low
Data Quality and Reliability	Data accuracy and completeness	Inaccurate or incomplete data sources	Compromises the reliability of diagnostic and predictive models	Implement data quality assurance mechanisms	High	High	Med
	Data latency and timeliness	Delayed data availability	Limits real-time monitoring and response capabilities	Improve data collection and transmission speed	Med	Med	Low
	Data integrity and verifiability	Unreliable data sources and manipulations	Undermines trust in the accuracy and authenticity of data	Implement data verification and validation	Med	Med	Low
Ethical and Legal Considerations	Algorithmic biases and fairness	Discriminatory or biased AI decision-making	Raises concerns of fairness and equity in healthcare outcomes	Develop and enforce guidelines for fair AI	High	Med	Low
	Informed consent and transparency	Lack of transparency in data collection	Undermines individuals' autonomy and choice	Enhance transparency and informed consent	High	High	Low
	Legal liability and accountability	Unclear responsibility in case of errors	Raises concerns about accountability and potential harm	Establish liability frameworks and mechanisms	Med	Med	Low

Infrastructure and Resource Constraints	Limited network bandwidth and capacity	Insufficient infrastructure for data transmission	Impairs real-time data analysis and communication	Improve network infrastructure and capacity	High	Med	High
	Limited computational resources	Insufficient computing power for data analysis	Hampers complex AI algorithms and predictive modeling	Upgrade computational resources	Med	Med	High
	Inadequate data storage and processing	Limited storage and processing capabilities	Hinders large-scale data storage and analysis	Enhance data storage and processing capabilities	Med	Med	Med
User Acceptance and Adoption	Lack of trust and awareness	Skepticism towards technology and data use	Hinders user acceptance and participation in smart systems	Educate and raise awareness about benefits	High	High	Low
	Technological literacy and accessibility	Limited knowledge and access to technology	Excludes certain populations from adopting and using smart systems	Improve technological literacy and accessibility	High	High	Low
Regulatory and Policy Frameworks	Lack of clear regulations and policies	Unclear guidelines and frameworks	Creates uncertainty and inconsistency in implementation	Establish comprehensive regulations and policies	High	High	Med

5.1. Interoperability and Standardization

The integration of AI, IoT, and blockchain technologies for pandemic diseases diagnosis in smart cities can lead to significant challenge regarding the interoperability, which result from the diversity in systems, devices, and platforms to ensure seamless communication and data exchange. Interoperability challenges can occur as a result of the heterogeneity of data formats, protocols, and interfaces used by different technologies. For example, AI algorithms may generate output data in various formats, IoT devices may use different communication protocols, and blockchain platforms may employ different consensus mechanisms [112]. Tackling these challenges involves the establishment of standardized protocols and data formats that assist the interoperability of these technologies. Moreover, embracing common data models, such as Fast Healthcare Interoperability Resources (FHIR), can enhance data exchange and interoperability between AI, IoT, and blockchain components smart city during pandemics control. To this end, Standardization can be regarded as a promising strategy to address interoperability challenges and foster the integration of AI, IoT, and blockchain for pandemic diseases diagnosis in smart cities. Standardization solutions may typically involve significant common frameworks, protocols, and data models that facilitate seamless communication and cooperation between various mechanisms. Public initiatives, such as the International Medical Device Regulators Forum (IMDRF) and the Institute of Electrical and Electronics Engineers (IEEE), are enthusiastically working towards developing healthcare-specific standards to ensure preserving data representation, security, privacy, and semantic interoperability. With the development of such common standards, smart city healthcare systems can guarantee compatibility, data consistency, and operational sharing of information between AI algorithms, IoT devices, and blockchain platforms [113]. On the other hand, the development of middleware and integration platforms is a promising solution that can offer mediators between different technologies, enabling elastic data exchange and communication between different components of pandemic control system in smart cities. These platforms can provide data transformation, protocol translation, and data orchestration services to bridge the gap between AI, IoT, and blockchain components. Furthermore, the application of standardized application programming interfaces (APIs) enables seamless integration and interaction between different technologies. Embracing open-source initiatives, such as Hyperledger Fabric and FHIR, can also promote interoperability by providing shared frameworks and tools for developers. More research efforts are required to address the interoperability and standardization challenges with more innovative standardization frameworks, and interoperability solutions to overcome barriers meeting the integration of AI, IoT, and blockchain in smart cities, thereby unlock the full potential of these technologies in improving pandemic control and response strategies [114].

5.2. Data Privacy and Security

5.2.1. Privacy Protection

The integration of AI, IoT, and blockchain technologies for pandemic diseases diagnosis in smart cities necessitates the collection and analysis of sensitive healthcare data. Ensuring privacy of these data is a major concern to the development of pandemic control systems is the collection of personal data for surveillance and contact tracing purposes. Smart systems rely on various data sources, including IoT devices, mobile applications, and public health databases, to gather information about individuals' health status, movements, and contacts. However, the collection of such sensitive data raises concerns about individuals' consent and control over their personal information. Privacy protections must be embedded into the design and operation of these systems, ensuring individuals' explicit consent, and providing clear information about the kinds of data collected, the drive of collection, and how the data will be used and protected. Striking a balance between effective pandemic control and safeguarding individual privacy rights is essential [115].

5.2.2. Data Security and Confidentiality

One pressing issue relating to safeguarding people's privacy involves maintaining confidentially during the collection and management of medical based personal data carried out under current pandemic situation throughout much of the world currently. To accomplish this requires taking care towards preventing unauthorized access or other purposely harmful efforts from causing breaches or circumvention illegally gaining unwanted viewership within their system. Thus, resulting we have come up with implementing cybersecurity measures such as access controls and encryption in order to build protective layers of security, plus taking care to use secure storage protocols. Additionally, it is necessary to ensure practices of strict confidentiality while exchanging data among various entities working on pandemic control systems through agreed upon shared data regulation executed through written agreements [116].

5.2.3. Data Retention and De-Identification

Privacy concerns arise from retaining and de-identifying personal data in pandemic control systems. While collecting data helps immediately address pandemics, clear guidelines for how long such information will be retained are critical. Retaining it longer than necessary risks breaching personal privacy by increasing the chances of unauthorized secondary use or re-identification. Smart cities should formulate a policy that prescribes a definite timeframe for retaining relevant pandemic information while ensuring its secure deletion or anonymization when no longer needed for COVID-19 control measures. Robust techniques like anonymous masking or grouping ensure individual rights remain preserved without impeding public health research and analysis efforts by upholding high standards of identifying withheld from these techniques by officials needing access only upon special requests. Thus, technology must prioritize strong measures preventing any compromise-related activities when managing privileged content continuously [117].

5.2.4. Security of IoT Devices and Networks

Incorporating IoT devices into smart cities has its drawbacks concerning security breaches since these gadgets attract hacking attempts and unauthorized access. Healthcare data becomes vulnerable once security is breached. Hence safeguarding IoT devices and networks requires implementing stringent measures such as authentication mechanisms, encryption protocols alongside timeless monitoring of access controls in IoT objects. Collaborative efforts are then crucial among relevant parties dealing with pandemics such as medical personnel cybersecurity experts and device manufacturers as noted standardization paves the way for enhanced safety of patients [118].

5.2.5. Trust in Blockchain Systems

The trust challenge in blockchain systems for pandemic control in smart cities stems from the need to ensure the reliability, integrity, and privacy of data. Blockchain technology offers inherent security features such as immutability and decentralized consensus mechanisms, which can enhance trust among participants. Nonetheless, numerous considerations need to be addressed to establish trust in the context of pandemic control. One of the main considerations is the design and audit of smart contracts on the blockchain. These self-executing agreements play a crucial role in automating processes and ensuring the accuracy of transactions. However, vulnerabilities or unintended consequences in smart contracts can undermine trust. Thorough design, rigorous testing, and regular audits are necessary to mitigate risks and ensure the secure execution of smart contracts. Another attribute is the equilibrium between data transparency and privacy. The immutability of blockchain can provide transparency and traceability, which is beneficial for auditing and accountability. However, in the context of healthcare and pandemic control, sensitive data privacy is of utmost significance. Striking a balance between transparency and privacy is critical to defend confidential healthcare information while leveraging the advantages of blockchain technology. Establishing governance models within the blockchain ecosystem is also vital for building trust. Clear roles, responsibilities, and access rights of stakeholders need to be defined to ensure accountability and prevent misuse of the system [75-78]. Transparent governance frameworks can enhance trust among participants and provide mechanisms for resolving disputes, managing updates, and enforcing compliance with regulatory requirements. Adopting the trust challenge in blockchain systems requires a comprehensive approach that encompasses the design and audit of smart contracts, the balance between data transparency and privacy, and the establishment of effective governance models [91-93].

5.3. Quality and Reliability Data

The integration of AI, IoT, and blockchain for pandemic diseases diagnosis in smart cities poses a great challenge in terms of ensuring accuracy and validity of the generated data. The sheer volume of information produced by IoT devices coupled with potential technical problems or human error can cause inconsistencies or inaccuracies in the collected data. Inaccurate readings can result from malfunctioning sensors whilst biased inputs can lead to incorrect predictions from AI algorithms. Data quality assurance mechanisms tailored towards validation checks as well as pre-processing techniques are imperative towards identifying errors at an early stage thereby mitigating associated losses. In addition to this, leveraging advanced techniques like detecting anomalies coupled with outlier analysis helps uncover outliers within invalid sections thus setting up systems for high accuracy standards across all stages [66].

Incorporating information from diverse sources, including IoT gadgets, electronic health records, and public health databases presents a few obstacles that relate to data integration and interoperability. Variances in data formats, diverse amounts of data granularity, along with the necessity for data fusion across multiple platforms and systems can make the process of integrating data more complicated. To achieve a seamless merging of this data requires addressing technical matters intricately such as harmonizing the data, achieving semantic interoperability as well as cross-platform information exchange standards. Through developing shared models of this data alongside standard interfaces and ontologies can also facilitate incorporating AI, IoT alongside blockchain components that will enable healthcare stakeholders' efficient collaboration alongside programming sharing. Additionally, establishments need to develop governance for this collected information to define their collective ownership rights as well as access and details regarding information sharing with other stakeholders involved in smart city healthcare systems [103].

The trustworthiness and provenance of data used in pandemic control systems are vital for ensuring reliable and robust decision-making processes. Data provenance refers to the ability to trace the origin, processing, and transformation of data throughout its lifecycle. Challenges arise when integrating data from multiple sources, as it becomes fundamental to establish the authenticity, reliability, and integrity of the data. Implementing data auditing mechanisms, timestamping, and digital signatures can enhance data trustworthiness and enable the verification of data authenticity. Furthermore, leveraging blockchain's immutable nature can provide an auditable trail of data transactions, ensuring transparency and accountability. Establishing data governance frameworks that encompass data quality assurance processes, data validation mechanisms, and data provenance tracking can contribute to enhancing data reliability and trustworthiness in smart city [109-111].

5.4. Ethical Considerations

Algorithmic biases and fairness are critical considerations in the application of AI for pandemic control in smart cities, which stems from the potential for AI systems to produce biased or unfair outcomes that can disproportionately impact certain individuals or groups. Tackling these issues is crucial to ensure equitable and effective pandemic control strategies. One of the main challenges is the presence of biased training data. AI algorithms learn from historical data, and if the training data is biased or unrepresentative of the diverse population, the AI system can perpetuate and augment those biases. In the context of pandemic control, this can lead to unequal access to healthcare resources, differential treatment, or disparities in disease detection and response. It is essential to cautiously curate and differentiate training data to minimize biases and ensure the fairness of AI algorithms. Another challenge is the lack of transparency and interpretability of AI algorithms [105-108]. Many AI models, such as deep networks, operate as black boxes, making it difficult to understand how decisions are reached. This lack of transparency raises concerns about the potential for hidden biases within the algorithms. To address this challenge, efforts should be made to develop explainable AI methods that provide insights into the decision-making process of AI algorithms. This will enable stakeholders to understand and mitigate biases and ensure fairness in pandemic control strategies. Furthermore, biases can also be introduced during the algorithm design phase. Human bias, conscious or unconscious, can inadvertently influence the development and deployment of AI systems. This can occur in various ways, such as biased selection of features, biased choice of training data, or biased assumptions embedded in the algorithm design. Recognizing and mitigating these biases requires diverse and inclusive teams of experts who can critically evaluate and challenge the assumptions and biases inherent in AI systems [113].

5.5. Infrastructure and Resource Constraints

The integration of AI, IoT & Blockchain technologies has revolutionized pandemic disease diagnosis in smart cities; however, it requires a scalable technical backbone for handling huge amounts of generated & transmitted data efficiently. Despite the benefits accrued from this technology-driven approach mitigating pandemics on unprecedented scales but many cities' inadequate infrastructures suffer from poor network coverage resulting in insufficient bandwidth leading towards latency issues reducing analysis timeframes affecting medical professionals' decision-making process [87]. Improving connectivity is fundamental hence investment into expanding both high-speed internet connectivity deployment & improving network coverage should be top priority areas towards overcoming these challenges successfully utilizing edge computing capabilities as well as adoption fog-computing technology nearer to the data sources highlighting reduction in latency while enhancing real-time processing capacity. For effective integration, the availability of sufficient resources is also vital; these include meeting computing power, storage & personnel requirements among many others. Challenges may arise in cities with limited resources both technological & financial. Consequently, securing adequate funding and resource collaboration between public and private sector entities responsible for implementing advanced technologies turn out to be increasingly important to achieve a successful pandemic response rate. Cost-effective solutions like shared infrastructure models or cloud computing has a great opportunity to alleviate resource constraints faced by smart city health care systems further implementing capacity-building programs including training initiatives would develop a skilled workforce capable of implementing these technological advancements efficiently achieving an increase in efficiency & medical care quality [101].

5.6. User Acceptance and Adoption

One of the key challenges in the integration of AI, IoT, and blockchain technologies for pandemic diseases diagnosis in smart cities is user awareness and education. Many individuals may be unfamiliar with these technologies and their potential benefits in healthcare. Lack of awareness and understanding can lead to skepticism, resistance, or reluctance to adopt these technologies. It is crucial to invest in public education campaigns, community engagement programs, and user-friendly information dissemination to raise awareness about the capabilities and advantages of AI, IoT, and blockchain in pandemic diseases diagnosis. Providing clear and accessible information about the functionalities, privacy measures, and potential impact on healthcare outcomes can foster user acceptance and encourage broader adoption of these technologies in smart city healthcare systems [112].

The user experience and interface design has a great opportunity in facilitating the acceptance and adoption of AI, IoT, and blockchain technologies in smart city healthcare systems. Complex or poorly designed interfaces can hinder user engagement and acceptance. It is essential to prioritize user-centered design principles, ensuring intuitive and user-friendly interfaces for healthcare professionals, patients, and other stakeholders. Seamless integration of AI algorithms, IoT devices, and blockchain systems should be accompanied by user-friendly dashboards, visualizations, and actionable insights that are easily understandable and accessible. Additionally, incorporating user feedback and conducting usability testing can help identify potential usability issues and refine the user experience, enhancing user acceptance and adoption of these technologies.

5.7. Regulatory and Policy Frameworks

The challenge of Regulatory and Policy Frameworks in pandemic control systems in smart cities arises from the requirement to establish clear and inclusive regulations and policies that govern the use of AI, IoT, and blockchain technologies. The rapidly evolving nature of these technologies, coupled with the urgency of pandemic control, presents unique regulatory and policy considerations that must be addressed. One of the focal confrontations is the lack of clear regulations and policies specific to the integration of AI, IoT, and blockchain in pandemic control systems. Existing regulations may not sufficiently cover the unique aspects of these technologies, such as data privacy, security, and algorithmic fairness. This creates uncertainty and inconsistency in implementation, hindering the effective and responsible deployment of these technologies. Policymakers must strike a sensitive balance between advocating the use of advanced technologies for pandemic control and ensuring the protection of individuals' rights, such as privacy, consent, and non-discrimination. The development of comprehensive regulations and policies that address these ethical and legal considerations is crucial for building public trust and confidence in the use of AI, IoT, and blockchain in pandemic control. Furthermore, the global nature of pandemics highlights the importance of harmonizing regulatory frameworks across different jurisdictions. Inconsistencies and discrepancies in regulations can impede the seamless sharing of data, interoperability of systems, and collaboration between smart cities. Establishing international standards and cooperation mechanisms can facilitate the development of effective regulatory frameworks that enable cross-border data exchange and collaboration in pandemic control.

6. Conclusion

This work explores the role of AI, IoT, and blockchain technologies in enabling sustainable pandemic control in smart cities through reviewing the immense potential of these technologies in revolutionizing healthcare systems and response strategies during pandemics. The integration of AI, IoT, and blockchain offers promising avenues for real-time monitoring, early detection of outbreaks, efficient contact tracing, and optimized resource allocation. Through exploiting advanced data analytics, smart cities can harness the power of big data to improve disease prediction models, advance public health infrastructure, and enable proactive interventions. The paper also explores the crucial challenges meeting this integration such as privacy concerns, data quality and reliability, ethical considerations, infrastructure constraints, user acceptance, and regulatory frameworks. Then, we explore significant opportunities for further advancements for refining and expanding the capabilities of these technologies, exploring innovative solutions for privacy preservation, scalability, and interoperability, and fostering collaborative partnerships to ensure sustainable and inclusive pandemic control strategies.

Supplementary Materials

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Not applicable.

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