


Article

Analyzing the Adoption Challenges of the Internet of Things (IoT) and Artificial Intelligence (AI) for Smart Cities in China

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Abstract: Smart cities play a vital role in the growth of a nation. In recent years, several countries have made huge investments in developing smart cities to offer sustainable living. However, there are some challenges to overcome in smart city development, such as traffic and transportation management, energy and water distribution and management, air quality and waste management monitoring, etc. The capabilities of the Internet of Things (IoT) and artificial intelligence (AI) can help to achieve some goals of smart cities, and there are proven examples from some cities like Singapore, Copenhagen, etc. However, the adoption of AI and the IoT in developing countries has some challenges. The analysis of challenges hindering the adoption of AI and the IoT are very limited. This study aims to fill this research gap by analyzing the causal relationships among the challenges in smart city development, and contains several parts that conclude the previous scholars' work, as well as independent research and investigation, such as data collection and analysis based on DEMATEL. In this paper, we have reviewed the literature to extract key challenges for the adoption of AI and the IoT. These helped us to proceed with the investigation and analyze the adoption status. Therefore, using the PRISMA method, 10 challenges were identified from the literature review. Subsequently, determination of the causal inter-relationships among the key challenges based on expert opinions using DEMATEL is performed. This study explored the driving and dependent power of the challenges, and causal relationships between the barriers were established. The results of the study indicated that "lack of infrastructure (C1)", "insufficient funds (C2)", "cybersecurity risks (C3)", and "lack of trust in AI, IoT" are the causal factors that are slowing down the adoption of AI and IoT in smart city development. The inter-relationships between the various challenges are presented using a network relationship map, cause-effect diagram. The study's findings can help regulatory bodies, policymakers, and researchers to make better decisions to overcome the challenges for developing sustainable smart cities.

Keywords: smart cities; sustainability; Artificial Intelligence (AI); Internet of Things (IoT); expert opinions; DEMATEL; emerging economy



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1. Introduction

The rapid migration of people to urban areas from rural areas is causing a burden on big cities. The city councils and local governments are facing issues in managing the essential needs of huge populations. On the other hand, global warming, climate change and technology's move towards renewable energy has pushed the revolution of smart cities, which aim to provide all essential needs to the public without causing many negative impacts on the environment. With the rapid development of science and technology

today, technological innovation has become a leading force in driving economic and social development. These advanced cities must use new technologies to improve their core systems to maximize optimization in all functions of city management by using limited energy. As an important carrier of economic and social development, cities are also the main gathering place of innovation factors, and the role of science and technology innovation in urban development is becoming increasingly prominent, and is becoming the engine of future development of cities [1]. Due to the recent industry achievements, the Internet of Things (IoT) and artificial intelligence (AI) are current popular research topics, and they have proven to return better results in many disciplines such as automating factories, public surveillance, asset monitoring, waste management, weather monitoring, etc. Combining IoT and AI is an effective way to intelligently upgrade the existing information systems.

Global economic crises can often lead to technological revolutions. For example, the world economic crisis in 1857 led to the first technological revolution, the world economic crisis in 1929 led to the second technological revolution, and the economic crisis in 1987 led to the information technology revolution [1]. After the financial crisis in 2008, smart cities have become a global trending topic (Figure 1) with the iconic report *Smart Planet* by IBM. *Smart Planet* advocates the full use of next-generation information technology in all industries [2], thus giving rise to concepts such as smart cities and digital cities. In the present day, the concept of smart cities is not clearly and statically defined [3]. However, it is clear through its interdisciplinary development that smart cities are deeply integrated with information and communication technology (ICT) and IoT [4]. The objective of smart cities is to enhance the efficiency of resource utilization, optimize city management and services, and improve the quality of life of citizens [5]. A smart approach with the help of AI and the IoT can be applied to smart transportation, security, energy, buildings, education, health, and more [4,5]. The smart city framework contains a large number of indicators to measure sustainability, such as social and economic sustainability, and AI and IoT technologies also help to maintain sustainability, so Khan et al. focused on the sustainable smart city and analyzed the challenges it faces [6]. Treude summarized the definitions proposed by several scholars for the sustainable smart city. He argued that finding a comprehensive, sustainability-oriented definition of a smart city is a complex challenge. Treude, therefore, proposed a limited definition: a city is smart if it uses smart technologies to better address 21st-century challenges. If it includes sustainable development goals, then it represents sustainable urban development [7].

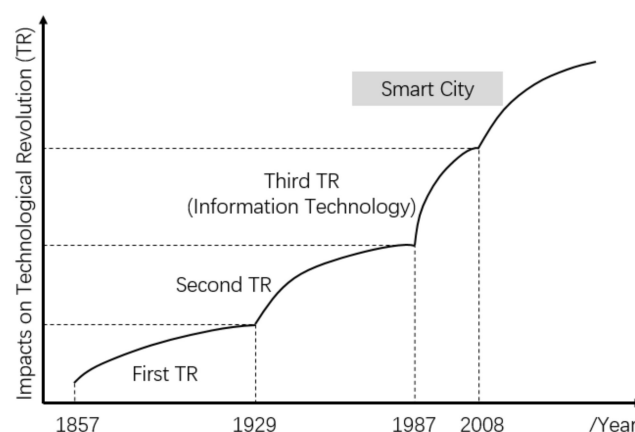


Figure 1. Impacts on technological revolutions by global economic crises (source: IBM, 2008).

Cities continue to attract new populations, and the United Nations estimates that by 2030, more than 60% of the global population is expected to live in large cities [8,9]. Population migration to large cities has become a common phenomenon worldwide. For example, the current resident populations of Beijing, Shanghai, and Shenzhen are all more than 20 million [10]. Huge population growth brings many impacts and challenges to

urban resources and services [8]. An analysis of public reports and government documents showed that in recent years, there has been an increasing number of smart city pilot projects in China (Figures 2 and 3). The increasing trend is indicated in Figure 2, which shows the number of China's smart city pilot projects, and summarizes the data from different years and integrates them into one form. The data for different years were from several sources, which are listed below the title of figure. They are China MOHURD, China NDRC, and Forward the Economist. China MOHURD is the Ministry of Housing and Urban-Rural Development of China. China NDRC is National Development and Reform Commission. Forward the Economist is one of the popular media and academic report analysis publishers in China. Sources provided by MOHURD and NDRC are government documents, while sources by forwarding the Economist are public reports. Refs. [11–18] are the lists of original data published by the cited source that are integrated into the figure. The original data from the above sources are separate, therefore the figure summarizes them and verifies the increasing trend.

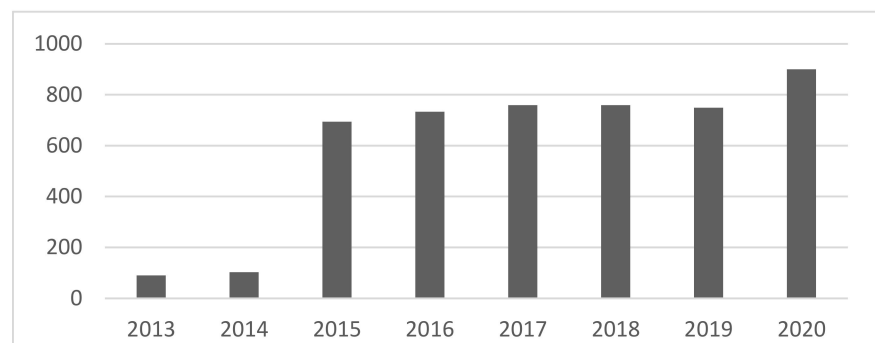


Figure 2. Number of smart cities with experimental policies in China (data source: China MOHURD, 2013, 2015; China NDRC, 2020; Forward the Economist, 2019, 2020, 2021).

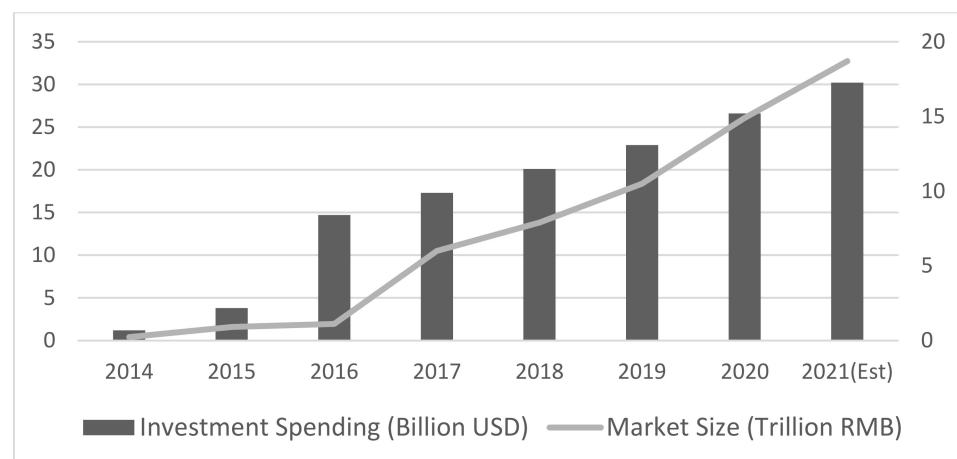


Figure 3. Trends for market size and investment spending of smart cities in China (data source: CCIT, IDC Qianzhan Industry Research Institute, 2019, 2020, 2021).

The idea of “smart” is to use information technology to drive the operation of the city, which includes monitoring, forecasting, and real-time management. The combination of IoT and AI can replace the traditional means of managers in the past, with IoT mainly referring to sensors or hardware, and AI mainly referring to back-end algorithms. With the advancement of technology and the increasing awareness of smart city residents, the concept of smart is no longer limited to intelligence, but fully incorporates the participation of residents or users. The mode of engagement includes not only citizen participation, but also decision making. Decisions must be made in a fast and effective manner, often relying on real-time feedback and behavioral changes from citizens [19]. Decisions are made

by top-down or bottom-up approaches, are technology or community-led, and include purposeful design or natural evolution. In well-functioning cities, citizens' decisions are dependent on multiple types of tools that guide them in their daily decision making [20]. According to IDC's *Worldwide Smart City Spending Guide* released in July 2020, China's smart city market spending will reach USD 25.9 billion in 2020, up 12.7% year-on-year, higher than the global average, and the second-largest spending country after the United States [21].

In recent years, due to the improvement of cloud computing technology, computers have been able to overcome the problems that used to occur due to the lack of arithmetic power. Artificial intelligence algorithms are being noticed by several industries due to the development of cloud computing, including the study of smart cities. Software, applications, and plugins are usually deployed on a cloud server and operated with cloud computing techniques. According to the investigation, for the Infrastructure as a Service (IaaS) category, the top five companies in the Chinese public cloud computing market are Alibaba Group (Aliyun), Tencent, China Telecom, Kingsoft, and Amazon Web Services (AWS). However, for the Platform as a Service (PaaS) category, the top five companies in the Chinese public cloud computing market are Alibaba Group (Aliyun), Oracle, Amazon Web Services (AWS), Microsoft, and IBM [22]. Wu summarized that from a functional point of view, the smart city system can be divided into a perception layer, a network layer, and an application layer [1]. According to Cohen, there are three stages in the development of smart cities: 1.0 Technology-Driven, 2.0 Technology-Enabled, and 3.0 Citizen Co-Creation. Different countries and cities are currently at different stages [23], and therefore they have different levels of adoption. The level of adoption reflects the degree of acceptance of technology in an object. It is a series of driving processes, from awareness to acceptance to use. This study aimed to examine the challenges hindering the adoption of AI and the IoT in smart city development by evaluating the current literature using the PRISMA method and incorporating expert opinions to select the appropriate barriers. Using the DEMATEL model, we developed cause-and-effect relationships between key AI and IoT implementation challenges. The findings of the study will be useful to understand the cause-effect relationships between the challenges that would help policy makers, practitioners, and researchers to understand the effect of the challenges in building smart cities in China.

2. Development of AI and IoT for Smart Cities

2.1. The Case for Smart City Development

Singapore is considered a pioneer in the smart city movement (Qi and Shen, 2019). Emerging technologies of IoT are used for the development of smart cities in smart fleet management, air quality monitoring, energy management, and smart agriculture needs with the help of sensors, robots, and other cyber-physical systems. All the generated data in this process are sent to the cloud (a central platform) for processing, and the output generated is used to plan smart city strategies [24].

In the context of Industry 4.0, the combination of smart cities with IoT and AI can lead to win-win results. Tobias' research highlighted the importance of monitoring systems [25]. In New York, for example, the government has upgraded its lighting system to enable intelligent control of dimming and turn-on times. It is also reducing lighting power by retrofitting LED installations. An automated meter reading (AMR) system is used to provide feedback on water usage, and also to monitor potential leaks in real time. Tobias also described the representative smart waste management, a technology that is also widely used in Singapore. As part of the smart waste management program, monitors on the bin lids collect information about the contents and location, and transmit the information to the waste team via a central server. The route of the waste collection team can then be optimized [26]. In Singapore, the Smart Nation vision was established in 2014 to harness new technologies to address growing urban challenges. To date, the most developed smart services in Singapore are the intelligent transport system (ITS), which is more than 10 years old, and e-government, which has been developed since the early 1980s [5]. In addition,

One Monitoring, developed by the transport department, provides services to all drivers and vehicle owners in the city, including access to information about cabs on the road and real-time road information, among other features [26].

In China, the Premier's report "Making Science and Technology Lead China's Sustainable Development" in 2009 opened the era of smart cities. Over the past decade, the smart city industry chain has involved interdisciplinary and multi-industries, integrating multilevel technologies. Based on the upstream and downstream industry chains of smart cities described by [21,27–29], this study integrated the industry ecosystems and technology architectures involved in smart cities. Figure 4 illustrates the streams (up, middle and down) for the integrated structure of industrial chains of a smart city. The vertical axis shows multiple layers, including upper terminal device, platform service, and the bottom infrastructure.

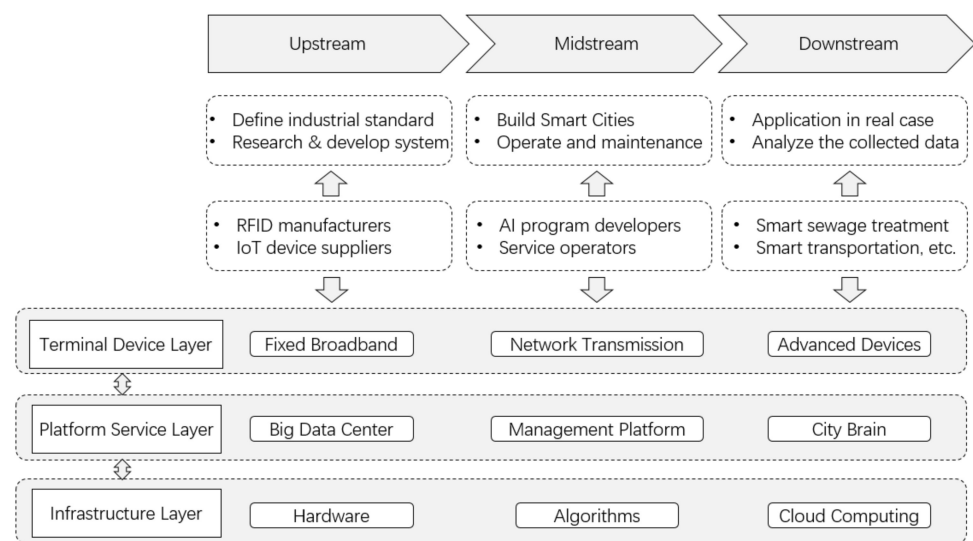


Figure 4. Integrated structure of industrial chains of a smart city (data source: Qianzhan Industry Research Institute, 2019, 2020, 2021).

As of 2019, there were more than 700 smart city pilots in China. The market size is growing by more than 30% per year, reaching RMB 10.5 trillion in 2019. Of these, up to 94% of provincial-level cities and 71% of prefecture-level cities have launched smart city programs [30].

Hangzhou proposed the City Brain system in April 2016. It is a digital interface for citizens, including 11 systems and 48 application scenarios such as police, transportation, cultural tourism, and health, with an average of more than 80 million data points per day [31]. The City Brain connects and shares data resources that were originally scattered in various departments and isolated from each other. By establishing a high-speed urban "CPU", the government's service effectiveness is continuously improved [31]. The City Brain has taken over the signals of 1300 intersections in a 420 km² area of Hangzhou. The functions that have been realized to facilitate people's livelihood include convenient parking, digital tourism, smart environmental protection, vegetable-planting base management, convenient access to medical care, and many other application scenarios. Therefore, the use of cutting-edge technologies such as big data, cloud computing, blockchain, and artificial intelligence to promote urban management means and management modes is a way to drive cities from digitalization to intelligence [30].

Shenzhen proposed the concept of "Building a Smart Shenzhen" in 2010, and is now one of the representative smart city models in China. Shenzhen is a mega city with more than 20 million people, so the scale of data and the way it is processed is very important. In the dimension of a smart city, "smart" means to have data, and that the data is connected [32]. To improve the efficiency of urban governance and industrial sectors, it

allows the sharing of effective data resources across sectors, industries, and fields, so that these integrated data and new technologies can improve capacity, output, and efficiency. For example, the Construction Digital Management Center (CDMC) was developed for metro construction sites. It enables centralized control of more than 400 construction sites across the city and uses AI algorithms to identify safety hazards, greatly enhancing work efficiency [32].

2.2. Features of the IoT

The Internet of Things (IoT) is a highly integrated and comprehensive use of next-generation information technology, which is important for a new round of industrial transformation and green, smart, and sustainable economic and social development [27]. New IoT applications are driving smart city initiatives around the world. The IoT is based on the installation of sensors (RFID, IR, GPS, laser scanners, etc.) for everything and connecting them to the Internet for information exchange and communication through specific protocols for intelligent identification, location, tracking, monitoring, and management [6]. The IoT and IT are at the core of the hyperconnected society, which is also known as Machine to Machine (M2M) or Internet of Everything (IoE) [33]. Theodoridis developed a city-scale testbed for IoT and future Internet experiments [34]. Latre et al. [35] developed the City of Things smart city testbed located in Antwerp, Belgium. The platform consists of a multi-wireless technology network infrastructure and includes an integrated approach that allows experimentation in three different layers: network, data, and living labs [35]. Sanchez deployed the Smart Santander project in the city of Santander, a typical application of the Internet of Things in a smart city [36].

Big data highlight openness and connectivity [37], and the combined application with IoT can moreover stimulate the value behind it. Chen et al. proposed a cloud platform architecture for building energy management based on big data and distributed technology using machine learning and environmental real-time analysis to provide technical support for building operations [38]. Zhang et al. summarized common data mining techniques, such as association mining, multivariable linear regression modeling, classification, clustering, and neural networks, and analyzed the data-mining techniques and the methods and trends of applying various data-mining techniques in the field of building energy efficiency [39]. Shi et al. used the SSIS algorithm with SQL to store historical data on energy consumption, and used Visual Studio as a development tool based on the ASP.NET MVC framework to establish an energy consumption management platform and energy consumption management software [40]. Yang et al. proposed a data-mining-based method for processing energy consumption data from public buildings, including building data sets based on historical data and classifying them according to different energy use patterns [41].

2.3. Implementation of AI in Smart Cities

As an important part of the smart city process, the construction industry plays a pivotal role. Technologies based on IoT and artificial intelligence algorithms have greatly accelerated the development of the construction industry. Artificial intelligence algorithms are a means of bulk problem solving [42]. At the same time, intelligent energy simulation tools combining parametric methods, BIM technologies, or computer programming techniques have emerged based on the architectural design perspective [43].

A smart city refers to a regional scale that aggregates multiple buildings. Therefore, the shared data of each building form the interconnection system. Building performance simulation technology can be used to rationalize or reduce the energy consumption of buildings. This method is called sensitivity analysis or parametric simulation. The combination of optimization algorithms to analyze changes in building energy consumption by changing several parameters simultaneously is called building performance optimization [44]. There are two main methods used to predict energy consumption in buildings, the data-driven approach and the physical modelling approach [45]. Due to the development of cloud

computing and algorithms, the data-driven approach has received increasing attention in recent years. The common machine learning algorithms are support vector machines (SVMs), artificial neural networks (ANNs), and decision trees.

Amasyali et al. reviewed the research on data-driven building energy prediction models, with a particular focus on reviewing the prediction scope, data attributes, and pre-processing methods in conjunction with machine-learning algorithms. Their study proposed future research directions in the field of data-driven building energy prediction. A brief overview of existing review studies on data-driven building energy prediction was presented by considering building type, time granularity, predicted energy consumption type, data type, element type, and data size [45]. For the machine-learning algorithms used to train energy consumption prediction models, the mainstream ANNs, SVMs, and DTs occupied 76% of the distribution, while 24% of the studies used other statistical algorithms, and some scholars also conducted comparative studies between two or more algorithms to derive similarities and differences in energy consumption prediction (Table 1). Nearly half (47%) of the studies focused on the prediction of overall building energy consumption [45]. A combination of multiple algorithms can be used to efficiently solve the problem of building energy consumption in smart cities. The below table summarizes the literature on building performance simulation and prediction in smart cities based on mainstream algorithms.

Table 1. Summary of algorithms mentioned by previous researchers for improving building performance management in smart city projects.

Scholars	Research Topics	Algorithms or Models
Sadeghi et al. [46]	Predicting residential building energy performance	DNN
Dong et al. [47]	Predicting residential electricity energy consumption	Combination of ANN, SVR, LS-SVM, GPR, GMM
Li et al. [48]	Predicting building electricity consumption	Optimized-ANN, PCA
Ahmad et al. [49]	Forecasting building electric energy consumption	ANN, SVM
Daut et al. [50]	Analysis of building electrical energy consumption prediction	Mixture of SVM and SI
Turhan et al. [51]	Comparative study of building heat load estimation	Combination of KEP-IYTE-ESS and ANN
Qiu et al. [52]	Simulation of vacuum photovoltaic glass and building energy consumption	Coupling ANN with light harvesting model
Zhong et al. [53]	Prediction of energy consumption in office buildings	SVM
Roldán-Blay et al. [54]	Prediction of building electric energy consumption	ANN and temperature profile model
Goyal et al. [55]	HVAC zone control for occupancy	MPC
Williams et al. [56]	Predicting monthly residential energy consumption	MARS
Massana et al. [57]	Short-term energy consumption forecasting for nonresidential buildings	MLR, MLP, SVR
Shi et al. [58]	Forecasting energy consumption in office buildings	ESN
Jovanović et al. [59]	Forecasting heating energy consumption for university campuses	FFNN, RBFN, ANFIS
Bourhnane et al. [60]	Smart building energy consumption forecasting and planning	GA, ANN

Abbreviations: Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), Deep Neural Network (DNN), Echo State Network (ESN), Feed Forward Neural Network (FFNN), Multivariate Adaptive Regression Splines (MARS), Multilayer Perceptron (MLP), Multiple Linear Regression (MLR), Model Predictive Control (MPC), Principal Components Analysis (PCA), Radial Basis Function (RBF), Swarm Intelligence (SI), Support Vector Machine (SVM), Support Vector Regression (SVR).

3. Literature Review and Challenges to IoT and AI Adoption in Smart Cities

The arrival of new technologies is always accompanied by opportunities and challenges. Although the concept of smart cities was only created less than 20 years ago, the rapid iterations and upgrades have brought about many challenges as well. This section identifies and summarizes influencing factors from a systematic literature review of published papers and studies. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was applied in the review process. PRISMA is a commonly used method that clearly presents the process and reasons of document identification, screening, inclusion, or exclusion, which can improve the accuracy of reviews and meta-analysis reports [61]. The initial source data was collected from major English and Chinese academic search engines, including Web of Science, Engineering Village, Scopus, Google Scholar, CNKI, and Wanfang Data. By using the identified keywords “IoT/ Internet of Things”, “AI/ Artificial Intelligence”, and “Smart City/ Smart Cities”; and “adoption”, “challenge”, “barrier” and their relative Chinese translations with Boolean structured searching methods, a total of 439 initial papers were collected. Then, 128 duplicated articles were removed. After reading the title, abstract, and keywords of those collected papers and determining whether they were aligned with the research topic, 87 of them that did not meet the criteria were removed. Then, a second measurement was done to check if the main content of those papers met the criteria, and whether they were articles, reviews, degree theses, or conference proceedings. After this step, 171 articles were included for further categorizing (see Figure 5). The final 171 articles selected based on the above bibliographic research were studied carefully to identify the potential challenges of AI and IoT adoption for smart city development. After analyzing the content of these articles, 10 influencing factors (challenges) were identified, and the supporting literature is presented in the Table 2. The roles and interrelationships of the identified challenges were established using DEMATEL by considering the experts’ opinions.

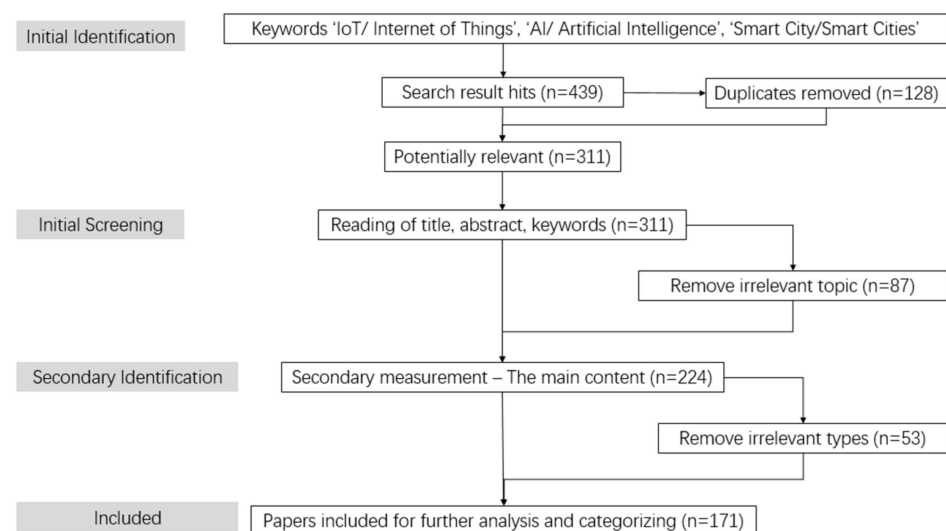


Figure 5. Literature search results using the Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA) method.

Table 2. Ten key challenges identified in the literature, with sources.

No.	Challenges (Factors)	Code	Reference
1	Lack of Infrastructure	C1	[62–73]
2	Insufficient Funds or Capital	C2	[74–91]
3	Cybersecurity and Data Risks	C3	[92–119]
4	Smart Waste and Hygiene Management	C4	[120–140]
5	Lack of Professionals	C5	[141–156]
6	Managing Energy Demands	C6	[157–176]
7	Managing Transportation	C7	[177–206]
8	Environmental Risks	C8	[207–232]
9	Managing Public Health and Education	C9	[233–244]
10	Lack of Trust in AI and IoT	C10	[229,245–265]

3.1. Lack of Infrastructure

Smart cities need the latest very advanced infrastructure, and every piece of equipment should be connected to the Internet to monitor it. In smart cities, connected IoT devices collect data from the physical medium to optimize decisions to improve urban services for citizens [266]. The growth of the population requires the need for housing, educational institutes, hospitals, and entertainment facilities. AI and the IoT should address the needs of infrastructure for all the people living in smart cities that will become part of the IoT infrastructure [267]. Artificial intelligence has important implications for achieving sustainable development, which is directly related to infrastructure development in emerging economies [268]. In addition, AI and the IoT should take care of utilizing and connecting the old (existing) infrastructure for multiple purposes. IoT technologies have contributed significantly to most of the detailed aspects of smart city technologies and infrastructures. As the basic concepts and ideas of IoT technologies are shared with smart city technologies and infrastructures, there are substantial business opportunities and extensive growth potential [269].

3.2. Insufficient Funds or Capital

A study showed that funds and budget were the main factors to begin any project [74,270]. The government or local authorities should have sufficient funds to design, develop, and continue smart city planning. Unavailability of funds delays the implementation of projects, which again causes an increase in project costs. Abdalla considers the lack of investment and capital funding as the main threat to smart city strategies [271]. AI and IoT techniques should help in prioritizing the projects based on the severity, requirements, timelines, and other parameters, and optimally allocate the budgets using the best optimization techniques [272–274]. To effectively address this issue, the government may need to obtain additional funding from entities in the private sector that are interested in these smart city projects [275].

3.3. Cybersecurity and Data Risks

Smart cities' interconnective networks create huge amounts of data containing rich information; bring innovation; and connect governments, industries and citizens. The data create a foundation for operating cities that will make them more effective and sustainable. Sharing and storing large amounts of actionable data also raises many concerns and challenges. This might include data related to citizens private information, government documents, and the information of all private organizations. On the other hand, cyber

insecurity raises concerns about data privacy and threats to smart city systems [273,274]. For example, there was a cyber attack on a top US pipeline network company, and the company was forced to shut down its operations for few days and paid a huge amount to the hackers to resume its operations [274]. On 20 August 2021, China passed a new personal data privacy law that will take effect on 1 November 2021 [275]. This law requires that separate consent be obtained from individuals for the processing of sensitive personal information such as biometric, medical health, financial accounts, and whereabouts. It also prohibits the collection of sensitive information from individuals in certain special cases of writing, such as facial information and biological information. This might create challenges for the tech giants to handle the information without mismanagement and misuse. Due to the increasing volume of sensors and their data, robust connectivity technology is a requirement for success. [245] Without powerful citywide coverage, the success of such a project is more than unlikely. Smart cities will house millions of people, and managing the people data, analyzing it, and preventing cyber-attacks is a challenge for AI and IoT. Therefore, an integrated approach is needed to deal with data security, user privacy, and trust in smart cities [276]. Meanwhile, the challenge of cybersecurity and data risks and the associated responsibilities must be shared by all parties involved in the smart city process, including city managers, residents, and the society itself. Cybersecurity and data risks comprise various types, and a cyber attack is one of the aspects. Therefore, effective measures have to be taken for smart cities to elaborate methods to detect attacks. Pasqualetti et al. have designed a centralized and distributed attack detection and identification monitor by describing monitoring limitations [277]. At the same time, they proposed a framework for cyber-physical systems, attacks, and monitoring. Carl et al. explored the capabilities of DoS attacks by analyzing denial-of-service attack detection techniques, including activity-based analysis, change-point detection, and wavelet-based signal analysis [278]. They argued that the detectors used for testing do not solve the problem independently, and that a combination of methods could produce better results in the future. Salem et al. surveyed insider attack detection and solutions in the literature [279]. Their approach was to classify insider attack detection cases. By summarizing the current common methods and techniques for insider attack detection, future research directions were proposed. Data security is particularly important in the medical field, and Liag et al. developed an attack detection model for medical surveillance systems using Internet Protocol (IP) virtual private networks (VPNs) over optical transport networks. They proposed a multilayer network architecture and a lightweight implementation of the procedure that enabled remote access to medical devices [280].

3.4. Smart Waste and Hygiene Management

There is a growing interest in the potential application of these technologies in manufacturing systems and municipal services to ensure flexibility and efficiency [120]. Handling waste still remains a major concern for many countries. Waste management from inception to disposal is one of the key challenges faced by municipal companies worldwide [281]. With the current phase of living styles in which most of the food and other items are wrapped with plastic or paper packaging, handling the waste produced by millions of people is a huge task. Waste collection must be completed within a specified time frame, as cities generate waste at an alarming rate and need to collect it more smartly [282]. Some waste management companies have developed AI-enabled waste segregation techniques that automatically separate different kinds of waste (e.g., paper, plastics, glassware, metals, etc.) automatically without human intervention. AI and the IoT should address the issues associated with collection, transportation, treatment, recycling, and disposal in waste management. For example, the intelligent disposal process was achieved through Ant colony optimization (ACO) technology. The entire process can be monitored centrally, thus providing high-quality services to the citizens of smart cities [283].

3.5. Lack of Professionals

The adoption of AI and the IoT require highly skilled professionals. Without proper experience and knowledge, organizations always misunderstand the benefits of these technologies. One of the current challenges facing smart cities is the lack of professionals with knowledge of computer technology and knowledge of different fields [141,142]. The unavailability of skilled professionals lags behind the adoption of AI and the IoT in sustainable smart city development [284]. Novák et al. provided a detailed analysis of the lack of professionals in the Middle East, Amsterdam, and Hungary [284–286]. The attraction and adoption of professionals will be particularly important in the post-pandemic era. The epidemic has already had an economic impact on the city, and if there is a chronic shortage, this will make it difficult to achieve intelligent urban management, and will affect the efficiency and quality assurance of smart city operations. For the construction of smart cities, the knowledge of professionals helps to achieve desired goals [287].

3.6. Managing Energy Demands

Smart devices are integrated and converted from everyday objects with advanced computing algorithms, and become the intelligent terminals that transfer data with a cloud server or other devices [288]. Thus, it requires a huge amount of energy to maintain the smart city [289]. Providing energy for a city's needs is a challenging task, and with increasing attention shifting towards renewable energy sources, several cities have struggled in migrating to renewable energy sources. On the other hand, energy demand and costs are increasing over time [290]. Domestic energy consumption is exponentially increasing due to the use of modern televisions, air conditioners, washing machines, smartphones, and computers. The technological advances and changes in consumer habits are leading to higher energy demands [291], and now the energy producers are looking for help from AI and the IoT to optimize the distribution of energy demands through methods such as automating streetlights, increasing unit electricity prices during peak times, and updating old equipment with modern equipment. AI implies new rules for organizing activities. There is a need to improve the design, deployment, and production of energy infrastructure to meet multiple challenges [292]. One solution to this challenge is to install solar power generation facilities for homes to help alleviate the energy consumption problem. Modern homes can also help boost the value of fixed assets by installing auxiliary solar power systems. Since solar panels do not generate electricity at night, homes will begin to draw power from the main grid as usual after the sun goes down. The Mississippi Power Company has announced a partnership with Tesla to create the world's first smart community with a Tesla residential solar+storage system [293]. Anbari argues that the combined use of solar and wind resources in a smart city environment can help energy companies to be able to meet the energy needs of cities [294]. Northfield argues that there is a need to maximize the use of the regional grids powered by solar, wind, or hydro energy so that the growing energy demands can be met locally instead of relying on a central supply line [295].

3.7. Managing Transportation

As a noteworthy part of today's economy, transportation accounts for 6–12% of a country's GDP that can be created. Although transportation has greatly improved our lives, many excessive problems remain unresolved [296]. Transportation has become the second-largest carbon-emitting sector due to inefficiencies. Current transportation methods are heavily dependent on crude oil products such as petroleum, diesel, etc. Electric cars are a good alternative to combat the emissions-related problems. Electric vehicles generate the necessary power for driving using a battery pack and electric motors. The charging requirements of electric vehicles can be met if existing fuel stations are upgraded to hybrid modes that provide petroleum products as well as e-charging stations. To avoid traffic congestion, it is important to design a city to minimize the public daily transportation requirement that can bridge the gap to reduce residents' travel times. One of the main branches of smart cities is smart transportation [297]. There is no smart city without a

reliable and efficient transportation system. This necessity makes intelligent transportation systems (ITSs) a key component of any smart city concept [298]. This affects not only smart transportation, but also the environment [299]. Saroj et al. developed a real-time, data-driven smart transportation simulation for smart cities. This simulation model was used to evaluate and visualize the feasibility of network performance metrics to provide dynamic operational feedback in a real-world, big data environment [300]. The machine-learning techniques that are an integral part of AI should be capable enough to analyze the past data from public and private transportation activities to analyze the root where frequent congestion occurs or where most accidents occur, the reasons for the accidents, and preventive measures to address these issues. In China, besides the smart taxi dispatch system for automobiles, there are also smart systems for bicycles, which is known as the shared bicycle. To improve the efficiency of shared bicycle use, the algorithm will propose a reasonable scheduling plan based on real-time road conditions, after which it will be carried out manually. Bicycle sharing is a solution to the “last mile” problem for residents, as many users choose to ride bicycles as an alternative to walking short distances.

3.8. Environmental Risks

Cities are becoming increasingly vulnerable to environmental risks and climate change [207]. In July 2021, several European countries and China experienced severe floods that caused millions of dollars of property damage and loss of people’s lives [207,301]. Smart cities should have highly responsive and agile disaster management systems such as weather monitoring, and alerting people regarding preventive measures to reduce pollution levels. Due to the increase in the number of inhabitants, there is a constant need to support economic growth to the point of creating environmental risks [301]. Large population concentrations also result in an increase in pollution from transportation, single-use plastics, and other types of waste, which largely contributes to environmental pollution [302]. Large-scale housing needs also pose several threats to the environment [303,304]. AI and IoT can be used in the design phase to minimize environmental risks. Automated drones have been used in various fields such as environmental risk detection and capture, traffic regulation, and air pollution monitoring. Air quality sensors on publicly accessible online platforms can support the measurement of environmental risks [305,306]. Urban environments improve competitiveness and respond to environmental risks to make cities smarter [307].

3.9. Managing Public Health and Education

By 2020, 86% of health-related companies will spend an average of USD 54 million on artificial intelligence and healthcare [308]. In China especially, which is home to the world’s largest population, providing healthcare facilities to all people is a challenge. It is difficult to provide the necessary medical requirements to all age groups without assessing their past health conditions. AI should learn to assess the health condition of a patient using their past medical records and present physical situation. The digitalization of medical records on a central server will help governments to assess the data anytime and anywhere in the country. This would help medical staff to investigate the patients and treat them carefully. Besides using a central server to store the medical records, there are also alternative methods using blockchain. Holbl et al. [309] have studied the applications of blockchain in healthcare, and marked it as an enabler for decentralized healthcare management. Kong proposed an AI-based model for online triage in sustainable smart city hospitals [310]. IoT-enabled medical equipment such as operation theatres, diagnostic tools, and smart equipment should assist in managing health. For example, during the COVID-19 pandemic, countries adopted measures for effective protocols for sharing health data. Allam argued that only by designing different smart city products to support standardized protocols that allow seamless communication between them can better urban structural risk management decisions be provided [246]. The flip side of the sensible use of new technology is the misuse of personal health data. Measures involving data collection and

use all inevitably trigger data breaches or misuse. The examples include personal journeys during the COVID-19 pandemic or records of visits for difficult medical conditions, which can compromise the rights of patients or even the general population. A new law enacted in China in August 2021 also prevents such incidents from occurring.

Education is also a primary need for the citizens. AI should help in the design and development of educational programs according to industrial and academic needs. Continuous revision of syllabi, assessment of student skills, and analyzing the industrial job requirements of developing skills in students are some examples in which AI can play a role. In this era of data abundance and exponential growth of new knowledge development, IoT is challenging institutions to rethink teaching and learning in the global marketplace [311]. The use of IoT can exchange and utilize information in very appropriate ways to facilitate student engagement and interaction with their peers and teachers. Mahmood explored the applicability of Raspberry Pi development boards or single-board computers in teaching enhancement, IoT technologies, and environments, and proposed a low-cost, efficient, and flexible educational platform [312]. Nuseir focused on entrepreneurial intentions in smart cities and elucidated the relationship between entrepreneurial competencies, entrepreneurial self-efficacy, and entrepreneurial intentions [247].

3.10. Lack of Trust in AI and IoT

Trust is generally located at the level of interpersonal relationships. In modern life, more particularly in smart cities, trust between people is increasingly systemic trust [248]. The lack of trust in AI and the IoT might slow their implementation in smart city development. As mentioned by researchers in [313,314], building the trust AI models that can transform social, political, and business environments and can help people in decision-making processes will remove any negative opinions about the usage of AI and IoT technologies. Government agencies should try to create awareness by spreading positive news about using AI in sustainable practices, maintaining transparency, and publishing some case studies that might improve the trust. The report “Artificial Intelligence and Life in 2030: One Hundred Year Study on Artificial Intelligence” by Stone et.al analyzed in detail how AI could impact a typical North American city in 2030 [315]. Each of these chapters and predictions for the next 15 years reflect the different AI impacts and challenges. Examples include the difficulty of creating secure and reliable hardware, the challenge of gaining public trust, and the social and societal risks of reduced human interaction. Poola mentioned simple tasks that AI can perform, such as facial recognition and car driving, as well as complex tasks such as developing a super AI that improves itself and triggers an intelligence explosion. It is also possible to use advanced technologies to eradicate poverty while also developing appropriate precautions for AI [316]. Kamble et.al provided an overview of AI and its applications in human life [317]. For example, they explored the current use of AI techniques in cyber intrusions to protect computers and communication networks from intruders. In the medical field, technologies are used to improve hospital inpatient care. Smart city data management systems provide the collected data and generate revenue, but the system should also maintain people’s trust while doing so [318]. Managing and building people trust is a key challenge in sustainable smart city development. Data- and citizen-centric smart city governance is essentially built trust [319]. However, Falco proposed the concept of participatory AI, and he argued that engaging the public will not only increase community trust in AI [249]. Hwang analyzed the evolution of smart cities in Korea. He argued that many Koreans have lost trust in smart city development due to their experiences with u-City [250]. However, the birth of new technologies can change this situation to some extent. The contribution made by the AEC (Architecture, Engineering, Construction) industry is indispensable to the process of building smart cities. Solearth and Zhao proposed the discipline of AEC-IT that integrates the AEC industry with advanced Information Technology in the era of the AI age [320]. Solearth and Zhao proposed a new view that currently, the stage of the AEC industry or architectural design sector is in the second half of the industry cycle, comparing with hundreds of years’ development. AI and

IoT play important roles in the process of AEC enterprises, from the original purely design service to DBOB mode (Design, Build, Operate, Brand) [320].

This section uses a systematic literature review approach to discuss the use of AI and IoT in smart cities. A total of 10 challenges were identified in the literature using the PRISMA method, and the number of articles published in the academic field and the number of smart city pilot projects were found to be increasing in the last few years. This growth pattern also was in line with the evolution of new technologies combined with the development and exploration of traditional industries. Moreover, the importance of algorithms, especially artificial intelligence algorithms, in this process can be reflected by combining the definition and use of smart devices. Therefore, how to develop efficient and secure algorithms is another hot research area that requires more attention. The importance of smart devices and algorithms is reflected by the fact that they are relevant to each of the influencing factors. Whether it is infrastructure, or water management, or health education, they are all relevant. The acquired influences and challenges will be investigated and analyzed later to determine the case of adoption.

4. Research Methodology

This section discusses the research methodology used in the study. We applied the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method to analyze and to identify the interrelationships between the challenges that are hindering the adoption of AI and the IoT in sustainable smart city development. DEMATEL was first employed in 1976, and it has managed to solve many global complex problems by considering experts' attitudes, and has become a widespread technique in decision-making problems [321,322]. DEMATEL is widely used in analyzing the barriers, challenges, and enablers in multiple disciplines. Recent studies have used DEMATEL for analyzing barriers in smart sustainable buildings [323], adoption of IoT [324], online food consumption [325,326], and supply-chain risk management [322,327]. The above literature emphasized the importance of DEMATEL in analyzing relationships between the challenges in various industries [61,328–331].

Figure 6 shows the various steps of the proposed methodology. There were three stages in the methodology. In stage 1, challenges for adoption of AI and IoT adoption in smart city development were identified using an extensive literature review according to the PRISMA method; in stage 2, industry experts having knowledge about the smart cities were contacted for collecting information about the challenges; and in stage 3, the collected data were analyzed, and the inter-relationships and ranking of the challenges are presented using the DEMATEL technique. Table 3 presents the profile of industry experts contacted in this study. A total of 10 experts from industries, government organizations, and universities were consulted for the data collection process. The data collection sheet was prepared in Microsoft Excel, and printed copies of the sheet were supplied to the experts. In some cases, the data sheet was sent over email to obtain the responses. The data analysis was done on a Windows-operated computer with an Intel i5 8th-generation processor with 8 GB of RAM and a 1 TB hard disk. The experts' selection was done based on a convenience sampling method. Experts with a bachelor's degree and at least two years of experience in domain knowledge of the environment, architecture, and IT roles in government and private organizations were considered. Experts with research publications and research interests in AI, smart cities, IoT technologies, and a willingness to share information were given preference. The data was collected from July 2021–August 2021.

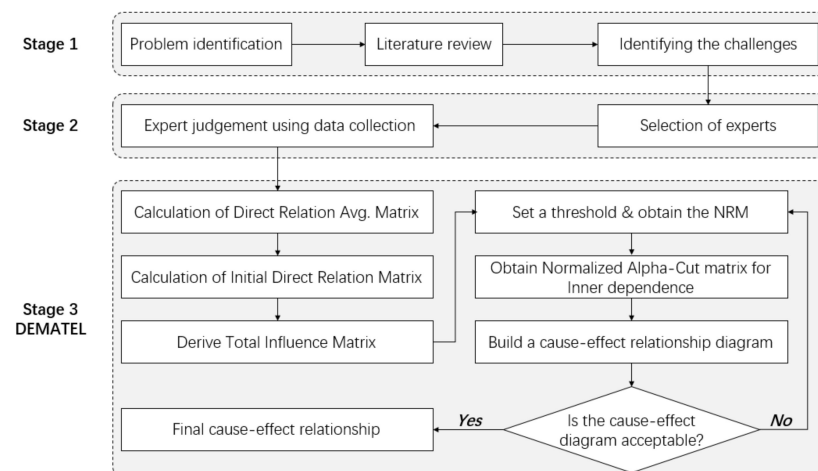


Figure 6. Roadmap of the research methodology.

Table 3. The linguistics evaluation for the assessments of the responders.

No.	Years of Experience	Education Level	Position in Organization	Type of Industry
1	6	PhD in Architecture	Associate Professor	University
2	4	Master of Education	Senior Lecturer	University
3	9	Master of Science	Start-up Founder	Technical Service
4	11	Bachelor of Economics	Analyst Manager	Business Consultancy
5	5	Bachelor of Information Systems	Technical Manager	IT
6	3	Master of Engineering	Intern	Construction
7	12	Master of Engineering	Cost Supervisor	Construction
8	7	Bachelor of Science in Environmental Studies	Administrator	Research Institute
9	5	Bachelor of Art	Senior Architect	Architecture
10	2	Bachelor of Engineering	Planner	Government

Various Steps in DEMATEL Methodology (Stage 3).

In the present study, 10 key challenges, including “Lack of infrastructure (C1)”, “Insufficient funds or capital (C2)”, “Cybersecurity and data risks (C3)”, “Smart waste and hygiene management (C4)”, “Lack of professionals (C5)”, “Managing energy demands (C6)”, “Managing transportation (C7)”, “Environmental risks (C8)”, “Managing public health and education (C9)”, and “Lack of trust in AI and IoT (C10)”, in the hindering of AI and IoT in the evolution of long-lasting smart cities were pointed out by reviewing substantial literature, as depicted in Table 2. A DEMATEL method (see Figure 5) was utilized to establish and analyze the causal linkages between the challenges.

We approached 10 industry experts (see Table 1 for profile details) to obtain information regarding the challenges to AI and IoT adoption for smart city development, and created a direct-relation matrix, M1, using the experts’ inputs and computing it according to the formula presented in Equation (1). The causality effect of one variable (challenge) on the other variable was collected using the matrix provided in Equation (1). For our convenience, the words, “challenge” and “variable” were interchangeable in the study.

$$A_p = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} & a_{15} & \dots & a_{1n} \\ a_{21} & 0 & a_{23} & a_{24} & a_{25} & \dots & a_{2n} \\ a_{31} & a_{32} & 0 & a_{34} & a_{35} & \dots & a_{3n} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ a_{(n-1)1} & a_{(n-2)2} & a_{(n-3)3} & \dots & \dots & 0 & a_{(n-1)n} \\ a_{n1} & a_{n2} & a_{n3} & \dots & \dots & a_{n(n-1)} & 0 \end{bmatrix} \quad (1)$$

where A_p represents the complete matrix information collected from one expert, N represents the number of challenges, and P represents the number of experts (10) contacted for the study.

Based on the scale provided in Table 4, the experts were asked to provide their recommendations in the given format. A five-point scale running from 0–4 was used by earlier studies [316,317] for analyzing the barriers using DEMATEL. This scale ran from 0 to 4 (0—no influence, 1—very low influence, 2—low influence, 3—high influence, and 4—very high influence), as depicted in Table 4. We computed the pairwise effect of each challenge with the other using this influence scale. For example, to determine the influence between “Insufficient funds or capital (C2)” on “Lack of infrastructure (C1)” all 10 of the experts’ inputs from the data collection table were extracted, and the values were 4, 1, 0, 4, 1, 4, 3, 4, 4, and 4, respectively. When computing an arithmetic mean of all experts’ opinions, we get $\frac{4+1+0+4+1+4+3+4+4+4}{10} = \frac{29}{10} = 2.9$, and this value was confined to a cell (1, 2) of a direct relation matrix (DRM), which is represented in Table 5. The value 2.9 indicated a significant effect of lack of funds on lack of infrastructure. Similarly, the influence between “Managing transportation (C7)” and “Insufficient funds or capital (C2)” could be calculated as $\frac{4+4+4+4+1+3+4+4+4+4}{10} = \frac{36}{10} = 3.6$, and was confined to a cell (2, 7) of the direct relationship matrix in Table 5, which also implied a significant effect of transportation management and the availability of funds. For another computation that showed the influence between “Managing public health and education (C9)” and “Insufficient funds or capital (C2)”, we get $\frac{3+0+0+3+3+3+1+0+0+0}{10} = \frac{13}{10} = 1.3$, which was specified in cell (2, 9) of DRM, and indicated a low or moderate relationship between the variables. As the same challenge could not have an effect on its own, all diagonal elements in the DRM were set to zero. Using the above procedure, all cells of DRM were calculated, and the results are shown in Table 5.

Table 4. The scale used for data collection for DEMATEL.

Please Put a Suitable Value in the Matrix Based on Your Experience	Score
No Influence	0
Low Influence	1
Moderate Influence	2
High Influence	3
Very High Influence	4

Step 1: Formation of a direct relationship matrix (DRM).

Table 5. The direct relationship matrix (M1).

Challenges	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0	2.6	2.3	2.6	2.5	2.7	2.6	2.8	2.7	2.8
C2	2.9	0	2	2.1	3.1	3	2.7	3.3	2.3	2.2
C3	1.6	2.3	0	2.6	2.5	2.4	1.9	1.9	2.2	2.1
C4	2.1	2.7	1.6	0	2.7	1.9	2.1	3	2.9	2
C5	2.6	1.9	2	2.8	0	3	2.9	2.6	2.8	2.2
C6	2.3	2.5	1.4	2.2	2.6	0	2.7	2.5	2.3	2
C7	2.1	3.6	2.1	2.7	2	2.9	0	2.3	2.5	1.9
C8	2.1	2.5	2.3	1.9	2.5	2.7	2.8	0	2.5	1.8
C9	2.5	1.3	1.9	2.6	2.8	2.5	2.5	2.3	0	2.8
C10	1.8	1.9	3.2	2.8	2.2	2.2	2.8	3.4	3	0

Step 2: Formation of a normalized direct relation matrix (NRM).

To prepare the data for the DEMATEL analysis, an NRM was prepared. The normalized direct-relation matrix “M2” (see Table 6) was constructed using the data based on the original direct-relation matrix. Each cell was divided by the sum of all cell values in that corresponding row. For example, for the DRM in row 1, the summation of all values (2.6, 2.3, 2.6, 2.5, 2.7, 2.6, 2.8, 2.7, and 2.8) equaled 23.6. Each cell in row 1 of Table 5 was

divided by this corresponding row total of 23.6. Then, the normalized values were obtained. Similarly, for all rows of the DRM, the normalization is done to obtain the NRM, which is shown in Table 6.

Table 6. The normalized direct-relation matrix (M2).

Challenges	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0	0.1079	0.0954	0.1079	0.1037	0.112	0.1079	0.1162	0.112	0.1162
C2	0.1203	0	0.083	0.0871	0.1286	0.1245	0.112	0.1369	0.0954	0.0913
C3	0.0664	0.0954	0	0.1079	0.1037	0.0996	0.0788	0.0788	0.0913	0.0871
C4	0.0871	0.112	0.0664	0	0.112	0.0788	0.0871	0.1245	0.1203	0.083
C5	0.1079	0.0788	0.083	0.1162	0	0.1245	0.1203	0.1079	0.1162	0.0913
C6	0.0954	0.1037	0.0581	0.0913	0.1079	0	0.112	0.1037	0.0954	0.083
C7	0.0871	0.1494	0.0871	0.112	0.083	0.1203	0	0.0954	0.1037	0.0788
C8	0.0871	0.1037	0.0954	0.0788	0.1037	0.112	0.1162	0	0.1037	0.0747
C9	0.1037	0.0539	0.0788	0.1079	0.1162	0.1037	0.1037	0.0954	0	0.1162
C10	0.0747	0.0788	0.1328	0.1162	0.0913	0.0913	0.1162	0.1411	0.1245	0

Step 3: Calculation of the total relation matrix (TRM).

Further, by taking into account the normalized direct-relation matrix (M2), a total-relation matrix (M3) was calculated by using the following equation:

$$T = X (I - X)^{-1} \quad (2)$$

where T represents the notation for TRM, X denotes NRM, and I denotes the identity matrix. Then using the procedure mentioned in [222], threshold values (α), D , and R were calculated, where D represents the sum of the values in a row, and R represents the sum of values in a column. Equations (3)–(5) were used to calculate the values D , R , α values:

$$D = [d_{ii}]_{n \times 1} = \left[\sum_{j=1}^n d_{ij} \right]_{n \times 1} \quad (3)$$

$$R = [r]_{1 \times n} = \left[\sum_{i=1}^n r_{ij} \right]_{1 \times n} \quad (4)$$

$$\alpha = \frac{\sum_{j=1}^n \cdot \sum_{i=1}^n r_{ij}}{n^2} \quad (5)$$

where i and j are the respective values for the rows and columns in the TRM, and n is the number of challenges in the study. The threshold values were used to determine the important and inconsequential challenges based on the threshold value. The α score was obtained as 0.9752, and the cell values in the TRM matrix that were smaller than the threshold α value (0.9752) were replaced with the value “zero (0)” in the α -cut TRM (see Table 7), and were ignored for further DEMATEL processing. The α value of challenges, which was equal to or greater than the threshold value, was updated in a new matrix called α -cut TRM (Table 8).

Table 7. The total direct-relation matrix (M3).

Challenges	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0.8878	1.0343	0.916	1.0695	1.0936	1.1181	1.1042	1.1496	1.1117	0.977
C2	0.9975	0.939	0.9062	1.0534	1.1153	1.131	1.1099	1.1675	1.0992	0.9574
C3	0.8074	0.872	0.6939	0.9126	0.9325	0.9431	0.9169	0.9496	1.0925	0.9374
C4	0.8815	0.9441	0.8093	0.8755	1.0023	0.9909	0.988	1.0532	1.0186	0.8634
C5	0.956	0.9802	0.9917	1.0444	0.9663	1.0946	1.081	1.1074	1.0818	0.9276
C6	0.8721	0.9221	0.7871	0.9419	0.98	0.8992	0.9905	1.0172	0.9797	0.8472
C7	0.9182	1.0153	0.8595	1.0159	1.0201	1.0668	0.9485	1.0727	1.0457	0.8954
C8	0.8814	0.9396	0.8334	0.9499	0.9954	1.0192	1.0121	0.9415	1.0047	0.8566
C9	0.8984	0.9023	0.8251	0.98	1.0097	1.0159	1.007	1.0348	0.9176	0.8959
C10	0.939	0.9921	0.9308	1.0574	1.0635	1.0805	1.0901	1.1476	1.1018	0.8549

Table 8. The α -cut total direct-relation matrix (M4).

Challenges	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0	1.0343	0	1.0695	1.0936	1.1181	1.1042	1.1496	1.1117	0.977
C2	0.9975	0	0	1.0534	1.1153	1.131	1.1099	1.1675	1.0992	0
C3	0	0	0	0	0	0	0	0.1614	0.1259	0
C4	0	0	0	0	1.0023	0.9909	0.988	1.0532	1.0186	0
C5	0	0.9802	0.1147	1.0444	0	1.0946	1.081	1.1074	1.0818	0
C6	0	0	0	0	0.98	0	0.9905	1.0172	0.9797	0
C7	0	1.0153	0	1.0159	1.0201	1.0668	0	1.0727	1.0457	0
C8	0	0	0	0	0.9954	1.0192	1.0121	0	1.0047	0
C9	0	0	0	0.98	1.0097	1.0159	1.007	1.0348	0	0
C10	0	0.9921	0	1.0574	1.0635	1.0805	1.0901	1.1476	1.1018	0

The α -cut total DRM was prepared by removing the matrix values less than the threshold value (0.9752), all the values that were less than α were assigned a 0 value, and all the values other than zero shown in Table 8 were considered to build the directed graph (digraph). The arrows in the digraph (see Figure 7) indicate the relationships between the challenges.

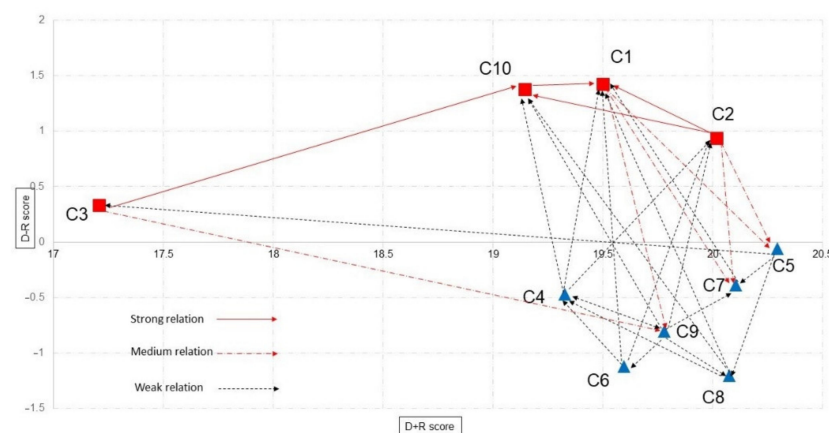


Figure 7. Directed graph showing the relationships between the challenges.

For example, the cybersecurity risks category is in the rightmost corner of the map, and it has only one arrow pointing towards it, which indicates that the challenge “lack of professionals (C5)” influenced “cybersecurity and data risks (C3)”. In addition, “cybersecurity and data risk (C3)” has two outgoing arrows towards “managing public health and education (C9)” and “lack of trust in AI and IoT (C10)”. The overall network graph analysis concluded that the other challenges had much less influence on the cybersecurity risks. The bidirectional arrows represent the dual relationship between the given set of challenges. The findings of R and D corroborated the degree of relationship effect among each critical

challenge. While $D + R$ represents the significance of a particular challenge, $D-R$ shows the net influence of the provided challenge. The $D + R$ score is plotted on the X -axis, and the $D-R$ score is plotted on the Y -axis to plot the cause–effect challenges on the scatter plot. For instance, for computations of $D + R$ and $D-R$ for challenge C1; the score of D was 10.462 and the score of R was 9.0393, so adding them together ($D + R$) equaled 19.50125, whereas subtracting them ($D-R$) equaled 1.4226752. The challenges with high $D-R$ values had a high importance, and were named as the “cause” group or causal challenges, and the challenges with low $D-R$ scores were less significant and influenced by the cause group challenges, and were named as the “effect” group challenges. All results are presented in Table 9.

Table 9. Prominence and relation results obtained by using the DEMATEL method.

Criteria Name	Code	D Score	R Score	D + R Score	D-R Score	Type
Lack of infrastructure	C1	10.462	9.0393	19.50125	1.4226752	Cause
Insufficient funds or capital	C2	10.477	9.5411	20.01761	0.9353911	Cause
Cybersecurity risks	C3	8.7706	8.4383	17.20887	0.3322851	Cause
Smart Waste and hygiene management	C4	9.4267	9.9004	19.32717	−0.473676	Effect
Lack of professionals	C5	10.116	10.179	20.29484	−0.062452	Effect
Managing energy demands	C6	9.2369	10.359	19.59631	−1.122412	Effect
Managing transportation	C7	9.8581	10.248	20.1064	−0.390191	Effect
Environmental risks	C8	9.434	10.641	20.07508	−1.207166	Effect
Managing public health and education	C9	9.4868	10.292	19.77877	−0.805249	Effect
Lack of trust in AI, IoT	C10	10.258	8.887	19.14481	1.3707933	Cause

As shown in Table 9, the barrier with a $D-R$ value less than zero was identified as an effective group, while a barrier with more than the $D-R$ value fell under the cause group. Based on the DEMATEL results as shown in Table 9 and Figure 8, the causal interactions and the degrees of influence among the AI and IoT adoption challenges in the smart city development are explained as follows. The challenges “C1, C2, C3, C10” were the main challenges affecting the implementation of various challenges for adoption of AI and the IoT in sustainable smart city development. Figure 8 displays the differentiation between the cause and effect groups. The challenges above the horizontal axis fell under the “cause” group, while the challenges below the horizontal line fell under the “effect” group.

Figure 7 displays the relationship between the cause–effect challenges; whereas the red colored solid lines show the strong relationship between the challenges, the red colored dashed lines indicate a moderate relationship, and the black colored dotted lines show the weak relationships. Researchers and organizations should assign prime importance to strong relationships, as understanding the connection between the challenges will help to overcome issues associated with the adoption of AI and the IoT in smart city development. To understand the relationships between the various challenges, we used NRM (see Figure 7), which displayed the weak, moderate, and strong causal linkages between all 10 challenges. The cause–effect relationships and their importance is explained in Section 5.

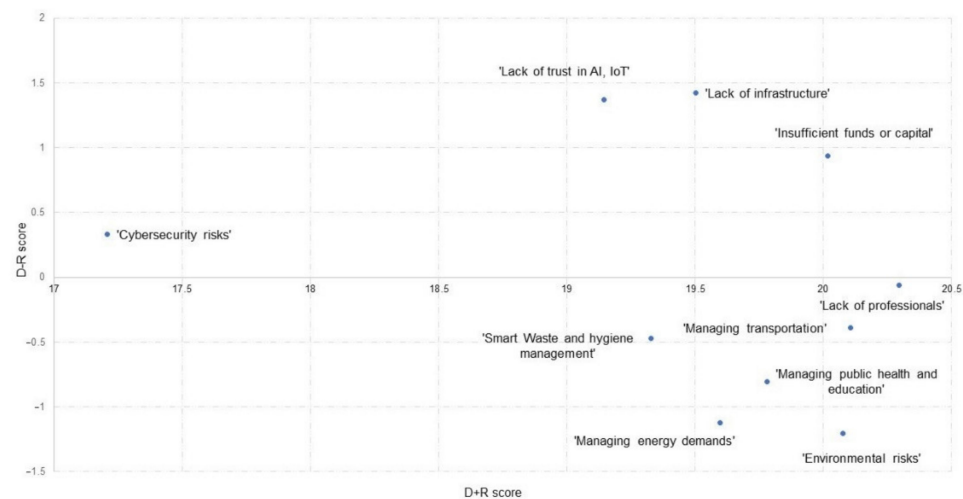


Figure 8. The cause–effect diagram.

5. Results and Discussion

The following section summarizes the findings based on the causal diagram (see Figures 6 and 7). As shown in Table 9, the challenges with a D–R value less than zero were identified as the “effect” group, while challenges with more than the D–R value fell under the “cause” group. The challenges, including Lack of infrastructure (C1), Insufficient funds or capital (C2), Cybersecurity risks (C3), and Lack of trust in AI, IoT (C10) were classified into the cause criteria group, while affecting the remaining challenges, which included Smart Waste and hygiene management (C4), Lack of professionals (C5), Managing energy demands (C6), Managing transportation (C7), Environmental risks (C8), and Managing public health and education (C9). Because cause variables have an impact on the effect group criterion, they should be given more attention while planning AI and IoT technologies in smart city development. The effect group challenges, although they had less dominance over the other challenges, were highly influenced by the cause group challenges. As mentioned in [328,329], cause group factors will have a strong relationship and high prominence. The factors that fall under the cause group are driving factors. The factors directly linked with cause group factors will have a high influence on these variables, and they have a strong relationship and low prominence. The factors (barriers) that are not connected to other factors will have no influence on or prominence in other factors.

The most important challenge in adopting AI and the IoT to achieve a large competitive factor in a sustainable smart city was “Insufficient funds or capital (C2)”, with the greatest D–R score of 1.422, implying that (C2) should be given greater emphasis in the entire system of IoT and AI implementation when designing an advanced city. This finding held true because recent studies have identified the unavailability of funds or financial resources as a major constraint for smart city transformation projects [69,332]. Furthermore, Table 9 reveals that the important effect degree of (C1) was 10.462, which ranked second-highest among all causative factors. In general, (C1) was a major element that requires further consideration during the implementation phase, and this finding also was supported by the literature [333]. With the second-greatest D–R value, “Lack of trust in IoT and AI (C10)” had a substantial influence on the other challenges. Lack of trust creates a barrier for building trust and promoting the use of AI and the IoT in smart city projects. One more important challenge identified from the analysis was “Cybersecurity risks (C3)”, with a D–R value of 0.3352, which also held in the context of smart city development. The interconnection and speed of the Internet and availability of vast public data makes smart cities vulnerable to cyber security attacks. An example of such a cyber security attack in the USA [334] was discussed in the introduction section of this study.

If the value of D–R was negative, the perspective belonged to the impact group (effects), and they were heavily influenced by cause group challenges. Furthermore, in terms of

notable effect degree, (C6) and (C8) were highly influenced by the cause group challenges. Similarly, the remaining challenges C4, C7, and C9 had low D-R values, which implied a significant low importance of these challenges in the smart city development in the context of AI and IoT adoption. In this study, “Environmental risks (C8)” had an R value of 10.641, the highest out of all challenges. Furthermore, when contrasted with other variables in the effect group, its D-R value was quite high (−1.2071). To understanding this trade-off clearly, a cause–effect diagram was used. In Figure 8, it can be observed that the challenge regarding environmental risks fell on the right side of the graph, which implied that even though the C8 challenge fell under the effect group, it had a substantial influence on the other elements. The D + R for “Managing transportation (C7)” was the second-largest in the entire procedure. Its D-R value was quite low, but “Managing energy demand (C6)” and “Managing public health and education (C9)” had the second- and third-highest R values of 10.359 and 10.292, respectively, as well as the second- and third-highest D-R values of −1.122412 and −0.8052, respectively. Both also can be considered on a priority basis. However, their D+R scores were lower than the other effect group criteria. The other components had mediated R values, indicating a high degree of effect. “Lack of professionals (C5)” had a negative influence on the system, since its D-R value was −0.0624. Other challenges had a major influence on it. The digraph of net cause and effect is shown in Figure 7, and it was used to demonstrate the relationship.

In addition, based on the M4 matrix results displayed in Table 6, we created a causal inter-relationship graph of the implementation of AI and IoT challenges in the development of the smart city and the interaction among these; key challenges are shown in Figure 7. The arrow-headed lines indicate the causal interactions among each pair of challenges. The red-colored labels are causal challenges, and the blue-colored labels represent the effect group challenges. It was found that “Lack of professional (C5)” had strong interactions with another challenge, “Managing energy demands (C6)”, while “Managing transportation (C7)”, “Environmental risks (C8)”, and “Managing public health and education (C9)” were further related by highly influencing, or having more interactions with, other challenges to the implementation of the IoT and AI in the development of a smart city (see Table 9).

According to this study, “Lack of infrastructure (C1)”, “Insufficient funds (C2)”, “Cyber security risks (C3)”, “Lack of trust on AI, IoT models (C10)” were highly dominant challenges that affected the other challenges. The organizations that are planning to implement AI and the IoT in smart city development should focus on these challenges first, as overcoming these challenges will facilitate the adoption process. The findings of the study will help to identify important challenges, and the relationship and influence of challenges also can be extracted. As a result, researchers and policymakers researching sustainable smart city development must address the major challenges to implementing IoT and AI.

6. Conclusions and Future Discussion

The concept of smart cities is becoming important to providing sustainable living conditions to people. Achieving sustainability is difficult due to the involvement of multiple factors. AI and IoT technologies can transform challenges and offer potential solutions to the issues perceived by society and regulatory bodies. This study aimed to identify and analyze the effect of important challenges that are hindering the adoption of AI and the IoT in sustainable smart city development. Initially, the challenges were extracted from an extensive literature review, then the DEMATEL method was used to analyze the relationship of causes–effects between the identified challenges. Data were collected from experts in diverse industries familiar with smart cities. Due to the rapid urbanization worldwide, cities are becoming overcrowded and are facing issues such as water scarcity, pollution, soil contamination, etc. On the other hand, unavailability of funds; global warming; and providing food security, basic health, and education are the key issues facing government bodies. Previous studies elaborated that AI and IoT technologies were useful in analyzing the optimization of resources using accurate data collection

processes. Developing plans for sustainable smart cities is a major challenge for emerging economies. Some countries (e.g., Singapore, Denmark, etc.) have leveraged the benefits of the AI and IoT techniques to measure and track various activities such as pollution levels, weather monitoring, energy distribution and management, traffic and transport management, water distribution and sewerage monitoring, etc. All the data collected by various sensors, cameras, videos can be sent to a central platform to perform an analysis to identify the issues and possible solutions using analytics. For example, the benefits of AI in traffic management to improve pedestrian safety is followed in Singapore [335], and Copenhagen uses an AI-enabled solutions lab to optimize energy usage and weather monitoring [335]. However, the majority of the smart city development is occurring in developed countries, whereas emerging economies such as China, India, and Brazil are still struggling to overcome the challenges in developing smart cities. The huge population and rapid urbanization rates are causing these emerging economies to design and develop sustainable smart cities at the present time.

Using the data from experts' opinions, the identified challenges were analyzed using the DEMATEL method. The challenges were grouped into cause types and effect types based on their importance as determined by the experts. Using the findings, we aimed to explore the relationships between the challenges and how they influenced the adoption of AI and the IoT in sustainable smart city development. Among all challenges, Lack of infrastructure (C1), Insufficient funds or capital (C2), Cybersecurity risks (C3), and Lack of trust in AI, IoT (C10) were the most prominent factors influencing the adoption of AI and the IoT in smart city development. Therefore, researchers and regulatory bodies should give importance to these challenges while planning a smart city project. In the causal loop diagram, it was observed that Smart waste and hygiene management (C4), Lack of professionals (C5), Managing energy demand (C6), Managing transportation (C7), Environmental risks (C8), and Managing public health and education (C9) were highly affected by the other factors. The relationships influencing these challenges can help us to understand the limitations and uncertainties associated with the other challenges. The results of this study can help academicians, industry practitioners, and policymakers reach an overall understanding of the inter-relationships between the challenges that are hindering the adoption of AI and the IoT in sustainable smart city development. The data were collected from experts from diverse industries and organizations, which made this study unique for emerging economies. A summary of the highlights of this study follows.

- We identified challenges for adopting AI and the IoT for sustainable smart city development using a systematic literature review method (PRISMA);
- Ten key challenges were identified using the PRISMA method, and a total of 171 articles were studied;
- Ten experts having experience in smart city development were contacted, and their opinions were evaluated using DEMATEL;
- The study findings revealed that lack of infrastructure, lack of trust in AI and the IoT, cyber security and data risks, and insufficient funds were the major barriers that are affecting the adoption of AI and the IoT for sustainable smart city development;
- The results of this study can be used as a basis for understanding various inter-relationships between the barriers, as the study was based on data from China and developing countries such as India, Brazil, and Malaysia can observe the findings as useful while adopting AI and the IoT for smart city projects.

Despite many efforts taken to carefully design the study, there were some shortcomings. We did not use a Grey scale to measure the accuracy of opinions of experts about the challenges, so in future research, Grey-DEMATEL with a greater number of challenges can be explored to achieve good results in this domain. ANP, AHP, or ISM can be used to present the hierarchical interrelationships more robustly. In addition, the consultation with experts with great experience in this domain can help reach possible solutions to overcome the challenges hindering sustainable smart city development.

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