



Comprehensive systematic review of information fusion methods in smart cities and urban environments

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ABSTRACT

Smart cities result from integrating advanced technologies and intelligent sensors into modern urban infrastructure. The Internet of Things (IoT) and data integration are pivotal in creating interconnected and intelligent urban spaces. In this literature review, we explore the different methods of information fusion used in smart cities, along with their advantages and challenges. However, there are notable challenges in managing diverse data sources, handling large data volumes, and meeting the near-real-time demands of various smart city applications.

The review aims to examine smart city applications in detail, incorporating quality evaluation and information fusion techniques and identifying critical issues while outlining promising research directions. In order to accomplish our goal, we conducted a comprehensive search of literature and applied selective criteria. We identified 59 recent studies addressing machine learning (ML) and deep learning (DL) techniques in smart city applications. These studies were obtained from various databases such as ScienceDirect (SD), Scopus, Web of Science (WoS), and IEEE Xplore. The main objective of this study is to provide more detailed insights into smart cities by supplementing existing research. The word cloud visualisation of machine learning/deep learning and information fusion in smart cities papers shows a diverse landscape, covering both technical aspects of artificial intelligence and practical applications in urban settings. Apart from technical exploration, the study also delves into the ethical and privacy implications arising in smart cities. Moreover, it thoroughly examines the challenges that must be addressed to realise this urban revolution's potential fully.

1. Introduction

The idea of "Smart Cities" has gained widespread recognition as a forward-thinking approach to urban development that strategically uses cutting-edge technologies to enhance residents' quality of life, promote sustainability, and improve service delivery [1]. At the heart of this transformative movement lies the integration of ML and DL techniques in conjunction with information fusion, which serves as the foundational

infrastructure of smart cities. This amalgamation of information and data-driven intelligence holds immense potential for enhancing urban living, making cities more sustainable, efficient, and responsive to the diverse needs of their inhabitants [2]. Concurrently, accelerating global urbanisation presents cities with increasingly intricate challenges, including traffic congestion, pollution, energy consumption, and public safety. These multifaceted issues necessitate innovative solutions, compelling cities to adopt a transformative approach that harnesses the

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power of data and technology. The transition towards smarter cities signifies a passing trend but a pivotal evolution in urban planning and governance, driven by the urgent imperative to establish livable and sustainable urban environments [3]. Currently, many academics are prioritizing the utilization of deep learning techniques to address the difficulties associated with forecasting and computing urban air quality, predicting urban population migration, and projecting urban water quality in intelligent cities. These models are generated by aggregating data from several sources, such as online weather websites, meteorological stations, taxi detectors, and other relevant sources. Moreover, urban big data comprises several types, such as text, symbols, and numerical values [4].

The effectiveness of information fusion in smart cities hinges on successfully addressing a range of critical issues. These encompass data heterogeneity, data quality control, privacy considerations, scalability, and the interpretability of machine learning models. In order to surmount these challenges and enable seamless integration of data from diverse sources, researchers and practitioners are actively engaged in developing innovative algorithms and frameworks. Their endeavours are targeted at efficiently resolving these issues, facilitating the effective utilisation of information fusion in smart cities [5].

However, this study comprehensively explores ML, DL, and information fusion methodologies within the context of smart cities, emphasising their significance and impact. It offers a comprehensive overview of previous research, facilitating the identification of gaps and the pursuit of new avenues by scholars and researchers. The findings of this study hold practical implications for technology experts, equipping them with insights to develop innovative smart city solutions. Policy-makers can leverage the study's insights to enhance public safety, energy efficiency, transportation systems, and sustainability measures. Furthermore, the study evaluates information fusion techniques for effective resource allocation, policy implementation, and infrastructure development, thereby empowering citizens to contribute to creating smart cities and making well-informed decisions actively.

The key points encapsulated in this review paper's contributions can be outlined through the following set of questions:

Question 1: What does the comprehensive review paper focus on regarding information fusion for smart cities?

Answer: The paper focuses on defining smart cities as a unique urban infrastructure incorporating intelligent sensors, IoT devices, and data. It explores information fusion methods specific to smart cities, emphasizing the crucial roles of IoT and data integration.

Question 2: What are the identified benefits, challenges, and potential research avenues discussed in the paper related to information fusion for smart cities?

Answer: The paper identifies benefits such as enhanced data integration, but also challenges like managing disparate data sources and handling large volumes in real-time. It discusses potential research avenues, emphasizing urgent issues and promising areas for exploration in the information fusion domain for smart cities.

Question 3: How does the paper address ethical considerations and the ongoing development challenges in the context of smart cities?

Answer: Ethical and privacy considerations are acknowledged, emphasizing the need for responsible development practices. The paper recognizes ongoing challenges in the development of smart cities and highlights the importance of addressing these challenges to fully realize their potential.

The paper structure is organised as follows: [Section 2](#) provides an overview of smart cities. [Section 3](#) presents the methodology for the systematic literature review. In [Section 4](#), a comprehensive science mapping analysis is conducted using a bibliometric approach to identify trends and gaps in the existing literature and deepen the understanding of the topic. The findings of the review, highlighting eight critical categories, are presented in [Section 5](#). [Section 6](#) discusses the enrichment of motivations, challenges, recommendations, and limitations in information fusion for smart cities. [Section 7](#) analyses five characteristics and research gaps to identify areas for future research and development in

the field of information fusion for smart cities. Finally, [Section 8](#) concludes this contribution.

2. Smart city: an overview

Smart cities employ technology and data-driven solutions to enhance urban environments' efficiency, sustainability, and livability. Improvements in sectors like transportation, energy, waste management, public safety, and healthcare are possible through data analysis, informed decision-making, and resource allocation. To achieve this, smart cities rely on information fusion, integrating diverse data sources to understand urban processes comprehensively. This comprehensive view enables the optimisation of resource allocation, enhancement of operational efficiency, and effective management across various domains [6]. The following points further illustrate this concept:

2.1. The smart city revolution

The smart city concept addresses the significant challenges faced by urban centres globally. The global population is increasingly concentrated in cities, necessitating innovative solutions to address the increasing need for efficient urban living. Smart cities utilise digital technologies and data-driven methods to enhance urban operations and services, reducing resource consumption and environmental impacts [7]. A smart city aims to integrate various sectors, such as transportation, healthcare, energy, public safety, and governance, into a comprehensive system. These cities enhance residents' quality of life, promote sustainability, and improve efficiency by integrating advanced technologies. The primary objective is to develop more livable, resilient, and adaptable cities to the changing needs of their inhabitants [3].

2.2. The power of machine learning and deep learning

The transformative power of ML and DL is mainly responsible for the smart city revolution. These subfields of AI focus on creating algorithms and models that can learn from data and make predictions or decisions based on this information. ML and DL are crucial in harnessing the vast data generated in smart cities. ML encompasses a variety of techniques, from traditional statistical methods to cutting-edge neural networks. It enables computers to recognise patterns, make predictions, and automate tasks based on historical data [8]. ML can be applied to numerous domains in the context of smart cities. For instance, it can optimise traffic management by predicting congestion patterns, enhance energy efficiency by analysing consumption data, and improve healthcare through predictive diagnostics. DL, a subset of ML, has gained prominence for its ability to handle complex and unstructured data, particularly images, audio, and text. Inspired by the human brain, deep neural networks can extract intricate features from data, enabling tasks like image recognition, natural language processing, and speech recognition. DL's applications in smart cities range from autonomous vehicles that navigate urban streets to systems that analyse social media sentiment to gauge public opinion [9].

2.3. Information fusion: the glue that holds it together

ML and DL are powerful techniques that enable us to extract insights and make predictions. However, we need to feed them with high-quality, varied, and timely data to achieve the best results. This is where information fusion comes into the picture. Information fusion, or data fusion, integrates information from multiple sources to provide a more comprehensive and accurate understanding of a given situation or phenomenon [10]. In the context of smart cities, information fusion is the glue that holds together the myriad data streams generated by various sensors, devices, and systems. These data sources include traffic cameras, environmental sensors, social media feeds, and more. Information fusion algorithms amalgamate this data to create a holistic view

of urban conditions, enabling more informed decision-making. For example, consider a scenario where a smart city is dealing with a sudden traffic congestion event. Multiple data sources, including traffic cameras, global positioning system (GPS) data from vehicles, and social media posts, can provide pieces of the puzzle. Information fusion techniques can combine this data to identify the cause of congestion, suggest alternative routes, and trigger adaptive traffic signal adjustments in real-time. This ability to synthesise information from various sources enhances the city's ability to respond effectively to dynamic situations [11].

2.4. The multifaceted applications of ML/DL and information fusion in smart cities

The utilisation of ML/DL and information fusion in smart cities encompasses a broad range of applications corresponding to the various challenges these cities tackle. In the following sections, we delve into critical domains where these technologies are exerting a significant and transformative influence [3]:

2.4.1. Transportation

One of the most visible and impactful domains of smart cities is transportation. ML and DL algorithms can analyse traffic patterns, predict congestion, and optimise traffic signal timing in real-time. Autonomous vehicles, which heavily rely on deep learning for perception and decision-making, are poised to revolutionise urban mobility, making it safer and more efficient. Information Fusion in transportation combines data from various sources, including GPS, traffic cameras, and sensors embedded in roads and vehicles. This fusion enables real-time traffic management and the development of intelligent transportation systems that can reroute vehicles based on current conditions and provide commuters with up-to-date information [12].

2.4.2. Energy management

Smart cities are committed to reducing energy consumption and carbon emissions. ML and DL play a crucial role in this endeavour by analysing energy consumption patterns and optimising the operation of city infrastructure. For instance, ML algorithms can predict energy demand, allowing for efficient energy generation and distribution scheduling. Information fusion in energy management involves integrating data from smart meters, weather forecasts, and building automation systems. This fusion enables cities to dynamically adjust energy distribution based on real-time demand and weather conditions, ultimately leading to energy savings and reduced environmental impact [13,14].

2.4.3. Public safety

Public safety is a top priority for smart cities, and ensuring it entails deploying ML and DL techniques. By analysing video feeds captured by surveillance cameras, ML and DL algorithms can identify suspicious behaviour patterns and trigger real-time alerts to law enforcement agencies. Moreover, these technologies can leverage historical crime data to forecast potential crime hotspots, facilitating the optimised allocation of resources. Information fusion plays a pivotal role in public safety by integrating data from diverse sources, including emergency calls, social media posts, and sensor readings that detect unusual sounds or chemical releases. This fusion of information enables a comprehensive and timely response to emergencies, ensuring the safety and well-being of city residents [15,16].

2.4.4. Healthcare

Smart cities are increasingly harnessing ML and DL in healthcare applications. These technologies can analyse electronic health records, monitor the health of residents through wearable devices, and even predict disease outbreaks based on epidemiological data and social media trends. This proactive approach to healthcare can lead to improved wellness and reduced healthcare costs. Information fusion in

healthcare involves integrating data from healthcare providers, wearable devices, and environmental sensors to create a holistic view of an individual's health. This fusion enables healthcare professionals to make more informed decisions and provide personalised care [17].

2.4.5. Governance and citizen engagement

Effective governance is at the core of any smart city's success. ML and DL can be used to analyse citizen feedback, sentiment from social media, and other data sources to understand public opinion and make data-driven policy decisions. Additionally, these technologies can optimise resource allocation for city services such as waste management and infrastructure maintenance. Information fusion in governance involves integrating data from citizen feedback platforms, social media, and municipal databases to view city operations and public sentiment comprehensively. This fusion facilitates evidence-based decision-making and enhances transparency in governance [18].

As our examination of ML/DL and information fusion in smart cities progresses, we embark on a more detailed exploration of specific applications and case studies that vividly demonstrate the transformative capabilities of these technologies. Furthermore, we meticulously scrutinise the ethical and privacy implications that emerge within the realm of smart cities while also addressing the challenges that must be surmounted to unlock this urban revolution's potential fully. By doing so, we aim to foster a comprehensive comprehension of how ML, DL, and information fusion profoundly shape future cities (see Fig. 1).

3. Methods

The analysis section of this study followed recommended reporting guidelines for a systematic review and meta-analysis approach (Fig. 1) [19,20]. The process involved conducting a thorough search across multiple bibliographic citation databases, encompassing various medical, scientific, and social science journals from diverse disciplinary domains. Specifically, four prominent digital databases were utilised to identify relevant papers: SD, Scopus, IEEE Xplore, and WoS. The SD is renowned for its reliable technology, science, and engineering sources. Scopus provides a comprehensive collection of reputable resources across various domains, including health, medicine, science, technology, and engineering. IEEE encompasses a vast array of technical and scientific literature, offering abstracts and full texts of papers in electrical engineering, computer science, and electronics. The WoS database serves as a valuable cross-disciplinary resource, incorporating research papers from diverse disciplines such as science, art, technology, and social science. By utilising these databases, which collectively cover a wide range of scientific and technological fields, this study ensures comprehensive coverage of relevant research, thereby providing researchers with valuable insights into the subject matter.

3.1. Search strategy

The present study systematically analysed English-language citations from 2018 to July 2023, utilising four databases (SD, WoS, IEEE Xplore, and Scopus). The objective was to identify relevant studies focusing on information fusion in the context of smart cities. To accomplish this, a carefully designed Boolean search strategy was formulated. This strategy involved identifying keywords associated with the application of ML and DL techniques in smart city domains such as "Transportation," "Public Safety," and "Urban Situations." Additionally, a comprehensive keyword encompassing these terms under the concept of information fusion was employed. By employing this systematic and comprehensive search approach, the study aimed to gather a diverse range of studies that explore the fusion of information in smart city environments, thereby shedding light on the subject matter.

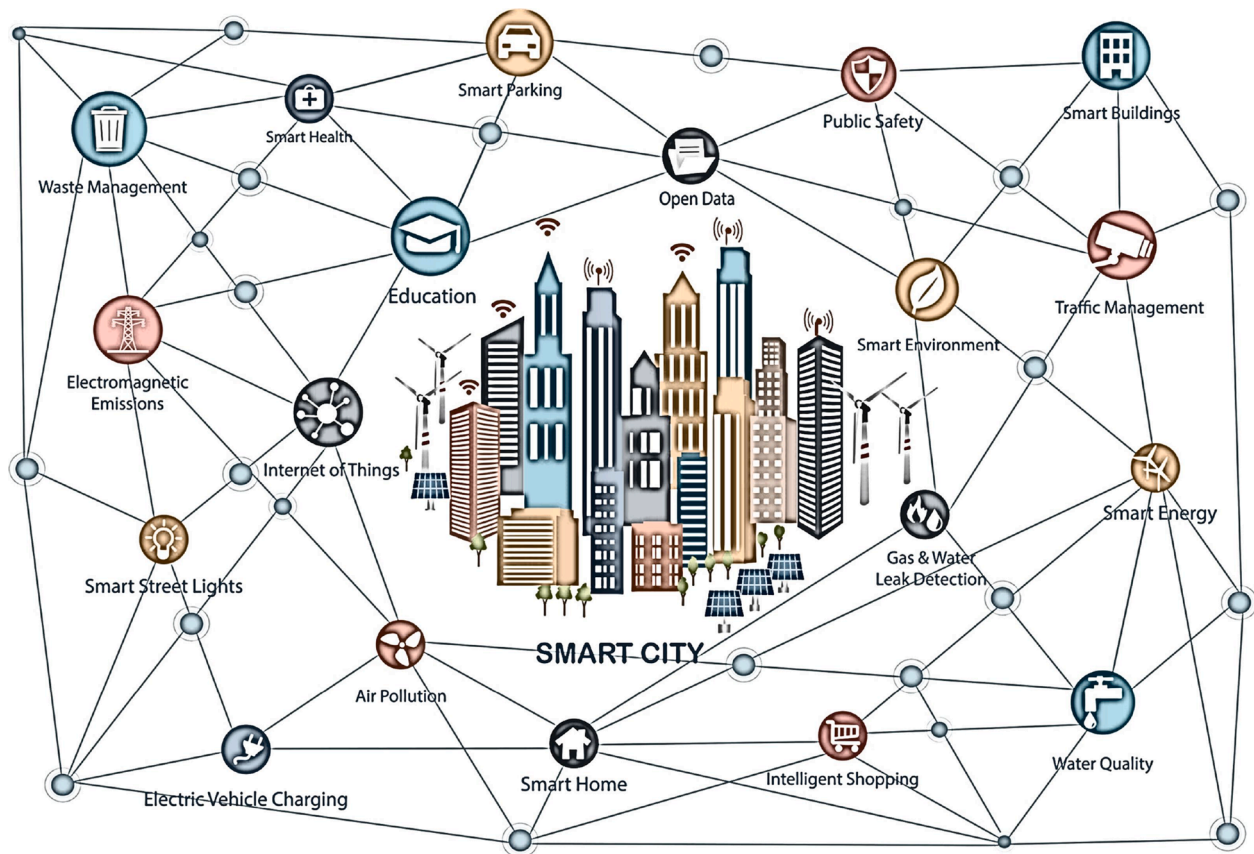


Fig. 1. Bird's-eye view of the smart city.

3.2. Inclusion and exclusion criteria

In systematic literature reviews, inclusion and exclusion criteria play a critical role as they provide clear guidelines for selecting studies based on specific criteria. These criteria are instrumental in ensuring that the studies included in the review align with the objectives and scope of the research, thereby enhancing the rigour and relevance of the findings. The present study considered the following criteria:

1. The paper was written in English in an academic journal or a conference paper.
2. The selected study must significantly relate to smart cities and prioritise information fusion in smart city components.
3. The article must contribute to data fusion in smart cities using ML/DL, ensuring high-quality and error-free content.

Conversely, the article's focus and relevance were maintained by using exclusion criteria to exclude studies that fell outside the predetermined scope:

1. Articles are written in a language other than English.
2. This article focuses on data fusion in smart cities, ignoring studies that only marginally discuss these aspects.
3. Review and empirical studies focusing on a specific hypothesis without a meaningful proposal are discarded.

3.3. Study selection

In adherence to the PRISMA declaration, as demonstrated in previous studies [19,20], this literature review employed a systematic approach comprising multiple steps. The initial step involved the removal of duplicate documents, followed by utilising Mendeley

software to scan titles and abstracts of the contributions. This process allowed for the inclusion of relevant works while excluding numerous irrelevant ones. The corresponding author addressed any author discrepancies, ensuring consistency. The subsequent step involved reading the complete texts of the selected articles and eliminating those that did not meet the predefined inclusion criteria. To ensure the accuracy and reliability of the filtering process, three experts independently assessed the efficiency of the filtering procedure (refer to Fig. 2).

The study encompassed articles that satisfied the established criteria, as illustrated in Fig. 1. The initial search yielded 287 articles, with 266 sourced from SD, 12 from Scopus, 3 from IEEE, and 6 from WoS. The publication dates of the collected papers ranged from 2018 to July 2023. Upon closer examination, it was determined that there were approximately 11 duplicate articles across the four databases, resulting in a refined set of 276 unique articles. Subsequently, a comprehensive review of the titles and abstracts was conducted, leading to the exclusion of 147 articles that were deemed beyond the scope of the study. This process yielded a final selection of 129 articles. These remaining articles underwent a thorough analysis through full-text reading, resulting in further refinement and consolidation, ultimately culminating in a final group of 59 articles. The meticulous reading of these papers enabled the researchers to understand the research topic at hand comprehensively.

4. A comprehensive analysis of science mapping

The growing number of studies and applied research have made it more challenging to identify critical evidence from earlier studies. Maintaining a comprehensive understanding of both practical and theoretical contributions has proven to be a significant challenge in the field of literature. Academics have proposed the PRISMA approach to organise previous study findings, identify problems, and pinpoint potential research gaps. By contrast, systematic reviews enhance the

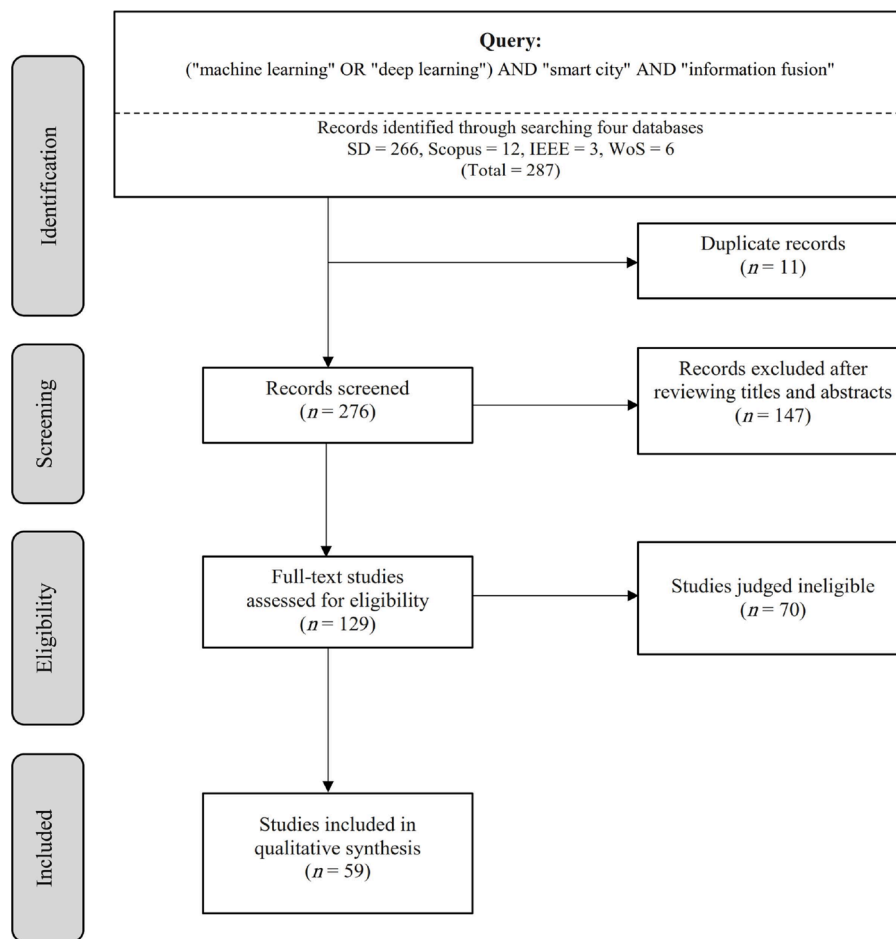


Fig. 2. A schematic of identifying, screening, and including relevant studies.

research plan, expand the knowledge base, and synthesise literature results, thereby expanding the overall knowledge base. However, systematic reviews face reliability and objectivity issues due to the authors' viewpoints, which can lead to the reorganisation of previous study

findings. Several studies suggest comprehensive science mapping analysis methods using R-tool and VOSviewer to enhance transparency in summarising previous study results [21]. The bibliometric approach offers reliable and transparent results, identifying research gaps and

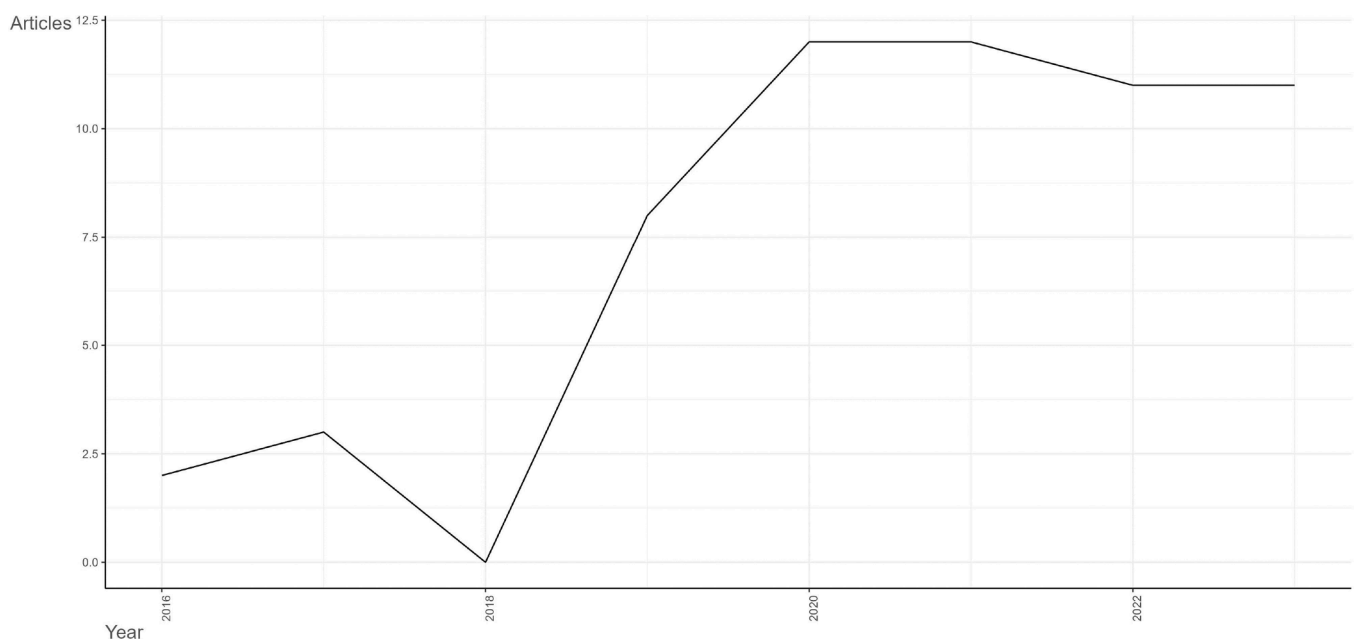


Fig. 3. Annual scientific production.

concluding literature findings with high reliability. In addition, the tools presented in this text are open-source and do not require high skills. Therefore, this study utilised the bibliometric method, detailed in the following subsections.

4.1. The production of annual scientific

In the last decade, there have been notable strides in the field of information fusion for smart cities, as evidenced by a substantial number of annual studies and publications dedicated to examining its utilisation, development, and resultant impact. This manifestation serves as a platform to highlight the continuous progress of research, the unveiling of novel findings, and the acquisition of fresh insights into comprehending and harnessing the potential of AI within immersive digital environments.

Fig. 3 provides a visual representation of the process involved in generating annual scientific output for systematic review articles. The data covers the annual scientific production of articles from 2016 to 2023, which is valuable for tracking the research output of various entities like research institutions, academic departments, or individual researchers. Between 2016 and 2018, there was a relatively low amount of scientific production, with only two articles in 2016 and three articles in 2017. However 2018, there was a significant decrease, with no articles being produced. This decline may be due to factors such as research projects taking longer to complete, funding constraints, or changes in research focus. In 2019, there was a notable increase in scientific production, with eight articles. This suggests a resurgence in research activities, potentially driven by increased funding or the completion of ongoing projects. From 2020 to 2021, research output was substantially increased, with 12 articles published each year. This indicates a consistent and productive period of research. It would be worth exploring if there were specific reasons for this spike, such as the availability of more resources or a shift in research priorities. From 2022 to 2023, the production remained relatively stable, with 11 articles published each year. This indicates a consistent research output compared to the peak years of 2020 and 2021. Overall, the trend suggests growth in the publication of papers focused on machine learning, deep learning, and information fusion in the context of smart cities.

4.2. Plot with three fields

A three-field plot is a technique used to display data with three distinct parameters. The text outlines the arrangement of text in a table,

with the title (TI_TM) in the left field, sources (SO) in the middle field, and keywords (DE) in the right field. The plot is frequently utilised to examine the correlations between the three parameters, as illustrated in Fig. 4. The analysis in Fig. 4 reveals that information fusion, future-generation computer systems, and signal processing are the most frequently used sources (SO) on the left side. The Information Fusion journal is also a crucial source (SO) that focuses on trustworthy and explainable AI. Furthermore, as indicated in the right field (DE), the keywords 'information fusion,' 'machine learning,' 'deep learning,' 'data fusion,' 'smart city,' and 'internet of things' are most frequently matched by the journals displayed in the middle field (SO).

4.3. A cloud of words

The word cloud has been instrumental in identifying the most frequently used and crucial keywords in previous research. Specifically, Fig. 5 presents the essential keywords that were compiled from the results of earlier studies to summarise a comprehensive image of them and reorganise information. Fig. 5 displays various sizes of keywords. The large size of the keywords indicates their higher frequency in the literature. Conversely, the small size of keywords suggests that they occur less frequently. According to the number of occurrences of terms, Fig. 5 reveals common topics in ML/DL and information fusion in smart cities, including information fusion, machine learning, artificial intelligence, data fusion, and deep learning, with smart cities being the most frequent. Other related terms, such as cloud computing, anomaly detection, artificial neural networks, blockchain, emotion recognition, energy efficiency, federated learning, intelligent transportation systems, the internet of things, reinforcement learning, sensor fusion, and spatio-temporal analysis, also have a relatively high frequency, indicating the importance of considering these aspects in developing and deploying AI systems. Fig. 5 also highlights some of the specific applications of AI in various domains, such as 5G IoT, activity monitoring, cyber-physical systems, affective computing, anomaly recognition, and appliance identification. The word cloud analysis of ML/DL and Information Fusion in Smart Cities papers reflects a diverse field covering technical AI aspects and practical urban applications. It highlights the importance of interdisciplinary collaboration, emerging technologies, and challenges like data integration, security, and sustainability. This intersection remains dynamic and crucial for improving urban living in smart cities.

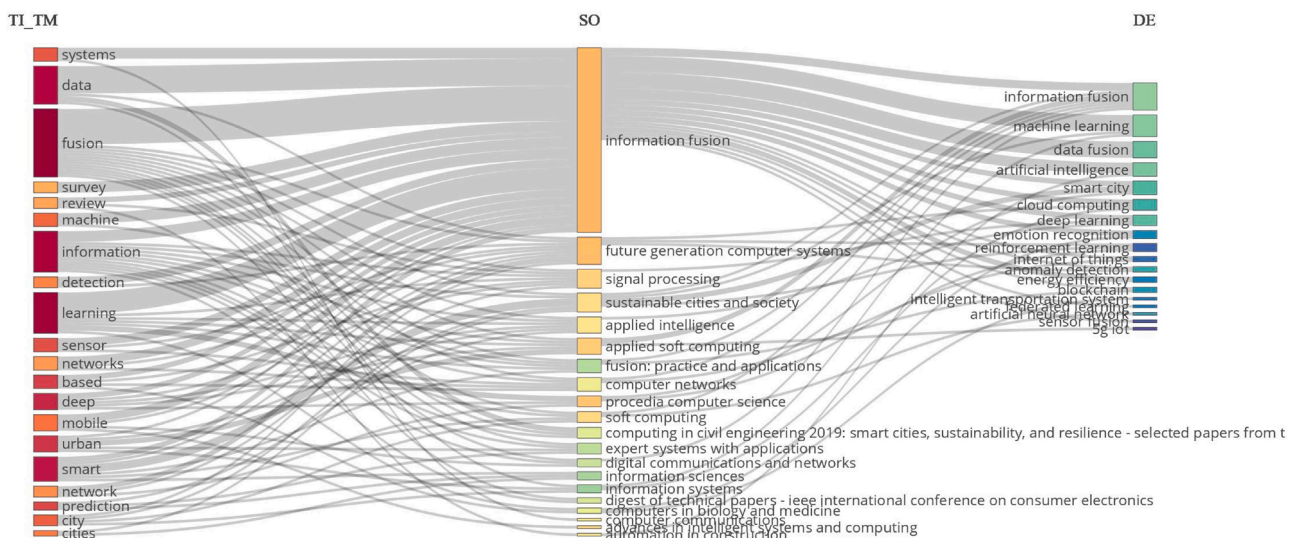


Fig. 4. A three-field plot: TI_TM on the left, SO in the middle, and DE on the right.

- 1) **Urban Situations in Smart Cities:** including 5 of 59 papers.
- 2) **Crowd Counting for Smart Cities:** including 2 of 59 papers.
- 3) **Improving Public Safety:** including 4 of 59 papers.
- 4) **Blockchain for Smart Cities:** including 2 of 59 papers.
- 5) **Machine Learning for Smart Cities:** including 13 of 59 papers.
- 6) **Smart Healthcare:** including 2 of 59 papers.
- 7) **Smart Transportation:** including 16 of 59 papers.
- 8) **Review:** including 15 of 59 papers.

The identified categories offer a comprehensive framework for the discourse on data fusion in the context of smart cities, presenting a wealth of insights that hold significant value for academic researchers and industry practitioners. These categories, as visually depicted in Fig. 7, serve as a valuable resource to delve into the multifaceted aspects of data fusion and its application in shaping smarter urban environments.

5.1. Urban situations in smart cities

A smart city refers to an urban area that utilises digital technology to enhance the quality of life for its residents. Within the scope of our analysis, we have identified 5 out of the total 59 articles that fall under this category. These selected articles specifically explore various aspects of smart cities, shedding light on the advancements and implications of employing digital technologies in urban environments.

In one study [22], a deep sequence learning model called the fire situation forecasting network is applied to enhance the processing of regional urban fire alarm datasets and predict spatial-temporal correlations related to fire incidents. Another research effort [23] focuses on leveraging inexpensive datasets to reconcile divergent urban environment images in Milano. The study explores the impact of spatial resolution and data complexity on achieving meaningful information fusion. Furthermore, a recent investigation [24] aims to improve the classification of urban acoustic sounds by employing deep feature transfer learning. The study combines hand-crafted features with deep networks to enhance the accuracy of sound classification in urban environments.

In the context of smart cities, a study [25] proposes a neural ODE framework for predicting urban flow. This framework enhances prediction accuracy and efficiency while reducing memory costs and model parameters. The study also investigates the influence of traffic volume factors on urban flow. Another research endeavour [26] introduces

ASTIF-Net, a deep learning framework designed explicitly for urban hotspot forecasting. By integrating multi-scale spatiotemporal information, this framework improves the accuracy of urban hotspot predictions.

5.2. Crowd counting for smart cities

Crowd counting involves using mechanical means to estimate the number of individuals in a crowd. This task presents significant challenges due to the diverse nature of crowd scenes, including variations in camera positions, crowd densities, and occlusions. Within this section, we have identified and included 2 out of the total 59 articles that specifically address the intricacies of crowd counting. These selected articles delve into the methodologies, techniques, and advancements in accurately estimating crowd sizes, considering the complexities introduced by different crowd scenarios.

In one study [27], the ghost attention pyramid network is proposed to address the challenge of scale variation in crowd counting. This method leverages the GhostNet architecture as an encoder and incorporates a zero-parameter channel attention module along with an efficient pyramid fusion module. By utilising these components, the study aims to improve crowd counting accuracy in scenarios with significant variations in crowd scale. Another study [28] focuses on developing a high-intelligence crowd density estimation algorithm that utilises convolutional neural networks (CNNs). This algorithm aims to enhance the accuracy and reasoning speed of crowd counting, making it particularly suitable for public security and smart city construction applications. By leveraging the power of CNNs, this study offers a sophisticated solution for estimating crowd density, which can have valuable implications for various domains requiring crowd management and analysis.

5.3. Improving public safety

Smart cities leverage technology to enhance various aspects of urban life, including public safety, crime reduction, emergency response efficiency, citizen satisfaction, and overall city sustainability and livability. Within our analysis, we have identified 4 out of the 59 articles that specifically delve into the advancements, strategies, and implications of implementing smart city solutions to address these areas. These selected articles contribute valuable insights into the utilisation of technology-

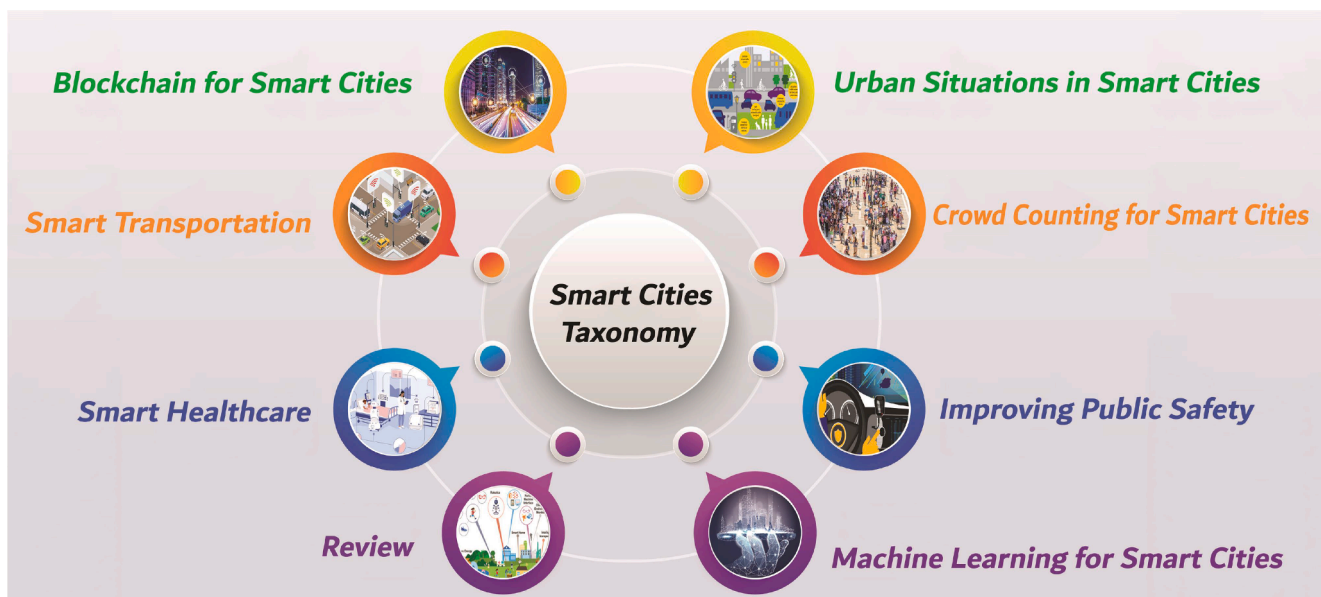


Fig. 7. Smart city information fusion taxonomy.

driven approaches to improve safety, enhance citizen experiences, and promote sustainable and livable urban environments.

In [29], an innovative approach is proposed to enhance traffic flow prediction in smart cities. The study suggests the utilisation of a deep reinforcement learning traffic-control system that leverages wireless sensor networks. This system incorporates an intelligent agent capable of optimising traffic control strategies to reduce energy consumption. Another research effort [30] introduces an AI-GFACN for optimising traffic flow prediction. This approach focuses on enhancing the semantic expressiveness of accident information and improving the accuracy of short-term traffic speed predictions. By leveraging AI-GFACN, the study aims to provide more precise and reliable predictions in the context of traffic flow management. Furthermore, in [31], a distributed machine learning framework is designed explicitly for intelligent Internet of Things (IoT) network management in smart cities. The research demonstrates the performance of this framework in vehicular sensor networks and explores potential scalable and collaborative extensions. The study highlights the significance of intelligent IoT network management for efficient operations in smart cities. Lastly, the study [32] investigates applying unsupervised machine learning techniques to detect decentralised anomalies in wireless sensor networks. The research evaluates the performance by considering neighbourhood size and spatio-temporal correlation factors. Additionally, the study explores conditions for neighbourhood data fusion and its impact on anomaly detection in wireless sensor networks.

5.4. Blockchain for smart cities

Blockchain technology plays a significant role in fortifying the security and privacy aspects of smart city applications by facilitating secure transaction recording and providing transparent and immutable records. Within this section, we have identified and included 2 out of the total 59 articles that specifically delve into the advancements, implications, and benefits of employing blockchain technology in the context of smart cities. These selected articles shed light on how blockchain enhances security and privacy, highlighting its potential to foster trust, accountability, and efficiency in various smart city domains.

A study [33] proposes a novel approach to address the challenges associated with high-order and multi-source heterogeneous data in cyberphysical social systems. The research suggests the utilisation of Tucker decomposition as an efficient method for data representation. By employing this technique, the study aims to enhance the handling and analysis of complex data structures, enabling more effective processing and interpretation within cyber-physical social systems. Another research [34] introduces a scheme called FusionFedBlock, which amalgamates blockchain technology and federated learning to bolster IoT security within the context of Industry 5.0. This scheme automates local learning updates, ensuring continuous learning process improvement while safeguarding privacy. Additionally, FusionFedBlock provides decentralised storage capabilities through a distributed hash table, further enhancing data integrity and accessibility within the IoT ecosystem. The study showcases the potential of FusionFedBlock as a comprehensive solution for enhancing security and privacy in Industry 5.0 scenarios.

5.5. Machine learning for smart cities

This section explores the use of machine learning techniques in smart city applications, including data analytics, sensor information fusion, anomaly detection, and emotion recognition. 13 articles out of 59 focus on machine learning's potential in optimising smart city operations, resulting in improved efficiency, effectiveness, and overall performance.

Several studies have been conducted in information fusion and data-driven decision-making for various applications. One study [35] presents a hybrid information fusion method that combines entity normalisation and data fusion techniques to analyse bridge inspection

reports, enabling effective maintenance decision-making. Another study [36] proposes an AI-based sensor-information fusion system that utilises deep supervised learning to process transportation data from different sensors. In the context of intelligent city communities, an IT-FCM approach [37] enhances clustering efficiency and accuracy by extracting smart data from continuously generated big data. Resource allocation in industrial IIoT environments is addressed in a study [38] that introduces a smart algorithm based on dual-attention deep reinforcement learning, offering scalability and flexibility. Emotion classification using physiological signals, environmental data, and location data is explored in another study [39] utilising deep learning techniques. A multi-agent architecture [40] is proposed for intelligent cities, which tackles social issues through the use of mobile sensing agents, virtual organisations, machine learning, and contextual information. An AIoT framework [41] is developed to detect anomalies in surveillance big video data using a two-stream neural network and cloud computing. Introducing PrivStream, a new study [42] presents an IoT streaming data inference platform that enhances real-time transmission speed, safeguards against untrusted servers, and filters sensitive data. Building information modelling-based cyber-physical systems is investigated in a study [43] for intelligent disaster prevention and structural system mitigation. Activity-as-a-Service, a framework integrating body sensor networks and cloud technologies, is explored in another study [44] for human activity recognition and monitoring in mobility. Object segmentation accuracy in Internet of Drones monitoring systems for smart-city monitoring is improved through a joint-learning scheme [45] that combines a CRF model and an improved U-net model. Additionally, a deep multi-scale information cross-fusion network for single-image super-resolution is introduced in a study [46]. Lastly, a recent study [47] proposes a wavelet transform-based 3D landscape design method for digital cities to enhance efficiency and address existing model defects.

5.6. Smart healthcare

Smart healthcare uses digital technologies for improved service delivery, utilising data fusion for disease diagnosis and personalised care. This section highlights 2 out of 59 articles that explore the advancements and implications of smart healthcare, highlighting its potential to enhance healthcare systems and patient outcomes.

In one study [48], a secure healthcare monitoring system is introduced, leveraging blockchain technology and intrusion detection systems (IDS) to detect malicious activity. This system aims to enhance patients' quality of life by ensuring the integrity and security of healthcare data, reducing stress levels, and lowering healthcare costs through efficient and reliable monitoring. By integrating blockchain and IDS, the study offers a comprehensive solution for safeguarding healthcare information and improving overall healthcare outcomes. Another study [49] presents a digital-twin smart healthcare system that utilises X-rays for COVID-19 diagnosis and detection. This system leverages the digital twin concept, which creates a virtual replica of the patient's condition, enabling accurate and efficient analysis of X-ray images. By harnessing the power of digital twin technology, the study aims to enhance the diagnosis and management of COVID-19, contributing to improved healthcare outcomes and effective disease control.

5.7. Smart transportation

Smart transportation uses digital technologies to improve transportation systems' efficiency, sustainability, and safety. 16 articles in a comprehensive collection of 59 articles highlight the integration of diverse datasets, optimising traffic flow, mitigating accidents, and enhancing overall performance.

Recent studies have demonstrated the efficacy of deep learning and machine learning methods for smart transportation. For instance, [50] presents a deep learning method for predicting city traffic speed using

geometric techniques and topological road network data. [51] employs collaborative computing and 5G IoT to predict bike demand at bike-sharing stations. [52] utilises artificial neural networks and support vector machines to predict traffic congestion on the Internet of Vehicles. In [53], a GSEN benchmark model for urban hotspot prediction addresses existing models' limitations and lays the groundwork for future smart city construction.

In the realm of smart city prediction, [54] presents LMST3D-ResNet for predicting electricity usage and traffic flow, while [55] suggests a multi-sensor information fusion method for IoT-assisted guided vehicles. [56] proposes an IoT-AGV plan for controlling the traffic of self-driving vehicles at intersections, highlighting the importance of sensor data and the automotive-into-the-loop model. [57] aims to create a deep reinforcement learning agent for regulating speed, collision avoidance, and lane-changing behaviour in connected autonomous vehicles.

For smart city management, [58] suggests a wireless geomagnetic sensor network for real-time vehicle identification in traffic scenes. [59] proposes a smart traffic control model using fog devices and cameras to detect driving violations. Ref. [60] aims to create synthetic pedestrian routes using multi-agent reinforcement learning and Google Maps data to understand mobility behaviour. Ref. [61] proposes MSTIF-Net, a deep learning method that accurately predicts urban ride-hailing demand by combining GCN, VAE, and Seq2seq structures.

Additionally, [62] suggests a deep spatio-temporal network framework for online ride-hailing demand prediction, while [63] proposes a fuzzy logic-integrated machine learning algorithm for smart parking and traffic management. [64] a deep learning-based hierarchical place recognition system is proposed to enhance smart city goals by facilitating easy navigation for locals and tourists. Finally, [65] proposes a machine learning-based intrusion detection scheme for mobile clouds that uses multi-layer traffic screening and decision-based virtual machine selection.

5.8. Review

The review paper on smart cities comprehensively assesses the existing research in this domain, shedding light on pertinent topics and pinpointing areas where further investigation is warranted; notably, within the corpus of 59 articles, a subset of 15 concentrates explicitly on the application of data fusion techniques in traffic management and environmental monitoring. This emphasis underscores the significance of data fusion in addressing critical challenges in these domains and catalyses proposing future research directions.

In [66], the authors review the evolution of multi-modal emotion datasets, encompassing an examination of feature extraction methods, scientific challenges, and future research opportunities. Building upon this, [67] delves into data fusion strategies to reduce energy consumption and promote sustainability in buildings. The study compares existing frameworks and introduces a novel method for electrical appliance identification. Complementing these efforts, [68] explores the literature on urban traffic management, addressing a research gap and providing insights into the field's benefits, drawbacks, future directions, and open issues.

Shifting focus, [69] examines multi-sensor data integration within integrated positioning systems, encompassing algorithms, architectures, scenarios, and design considerations. Expanding the scope, [70] delves into the "Smart City Data Science" domain, identifying ten future research topics critical for data-driven smart cities. Additionally, [71] explores deep learning-based sensor fusion techniques employed in medical imaging, autonomous driving, remote sensing, and robotics, highlighting challenges and future directions.

Further broadening the landscape, [72] delivers a comprehensive overview of medical signal fusion methods for intelligent healthcare applications. [4] evaluates data fusion performance in smart city applications utilising multi-perspective classification and discusses future directions and challenges. [73] serves as a tutorial on multi-modal data

and machine learning techniques for emotion recognition. Simultaneously, [74] delves into mobile edge caching, data traffic processing, performance indicators, machine learning, optimisation methods, practical applications, research problems, and prospects.

Ref. [75] evaluates the use of machine learning algorithms in wireless sensor networks. It examines their advantages, disadvantages, and impact on network lifetime parameters. In addition, [76] discusses recent developments, datasets, models, and machine learning prospects in fusion data-driven Earth observation algorithms. Shifting focus, [77] analyses academic publications to identify benefits and research topics associated with adopting AI in construction engineering and management. Furthermore, [78] explores advanced IoT sensor anomalies, intelligent sensing techniques, and data fusion problems. Lastly, [79] presents a comprehensive IoT optimisation framework that employs IoT and AI technologies to enhance the diagnosis of obstructive sleep apnoea.

6. Discussion

In this section, an in-depth exploration is undertaken to examine the underlying motives, challenges, and limitations encountered by current and past researchers in the field of information fusion for smart cities. Additionally, the authors provide valuable recommendations and insights for future work that are crucial to uphold the credibility and advancement of this domain. A comprehensive understanding of these aspects is achieved through a rigorous analysis of these aspects, paving the way for further progress and innovation in the field of information fusion for smart cities.

6.1. Motivations

In the rapidly evolving landscape of urban transportation and data management, several key themes have emerged as drivers of innovation. Data fusion techniques are revolutionising how disparate data sources are integrated to enhance decision-making. Urban data advancements provide cities with valuable insights for more efficient planning and resource allocation. The IoT and data integration are pivotal in creating smart, interconnected urban environments. Transportation services and optimisation are at the forefront of leveraging these technologies to improve mobility, reduce congestion, and enhance urban livability (see Fig. 8).

6.1.1. Data fusion innovation

Information fusion techniques play a pivotal role in addressing the motivations posed by the ever-expanding landscape of data-driven predictions. In [35], it is highlighted that these techniques are essential for resolving conflicts, mitigating ambiguity, and managing uncertainty that often arises when extracting information from diverse sources. This becomes particularly relevant in domains like intrusion detection in mobile clouds, as discussed in [65]. Here, machine learning-based approaches are called for to create robust intrusion detection systems that can adapt to heterogeneous client networks while



Fig. 8. Motivations diagram.

offering customisable computational complexity. Notably, such systems should operate without the burden of frequent rule updates.

Extending the scope of healthcare, as mentioned in [48], early identification of medical conditions has become increasingly critical. Integrating federated learning with intrusion detection systems presents an innovative approach to improving healthcare outcomes. This approach could enhance diagnostic accuracy and treatment planning by allowing distributed healthcare data to be used collectively while preserving privacy. Meanwhile, [49] underscores the pressing need to address security challenges within healthcare systems, especially in light of the COVID-19 pandemic. Strengthening data security and privacy measures and exploring digital twin approaches can help healthcare systems become more resilient and capable of responding to emerging threats effectively. These interconnected motivations underscore the importance of information fusion, machine learning, and innovative solutions in data-driven fields such as healthcare and cybersecurity.

6.1.2. Urban data advancements

Urban data analysis and its integration into the development of smart cities have become increasingly significant in recent years. One critical aspect is the affinity between urban data and the potential for automatically revising or semi-automatically generating outdated datasets using new data sources [23]. This approach is essential for ensuring that urban data remains accurate and relevant over time. Another critical area of focus is integrating and analysing big transportation data, which is generated and collected from various sensors [36]. Analysing this data can provide valuable insights into transportation patterns and enable more efficient and sustainable transportation systems in smart cities.

Moreover, it is crucial to address the demand for an iterative deep-learning approach capable of selecting sensor signals from various modalities based on their size [39]. This approach can optimise data collection and processing in smart city environments. Intelligent transport systems using IoT technology are in high demand to mitigate traffic congestion and improve transportation efficiency in smart cities [52]. These systems leverage data from various sources to enhance urban mobility. Furthermore, developing deep learning algorithms for region-based predictions in smart cities is essential [54]. These algorithms can assist in various urban applications, such as predicting traffic flow, energy consumption, and environmental conditions. Improving smart transportation overall is a top priority in the context of smart cities [55]. Utilising multiple sensors and data sources to minimise travel time is a crucial strategy for achieving this goal [56].

Additionally, vehicle cameras for smart traffic management can enhance safety and efficiency [59]. Energy efficiency is another critical concern, and there is a need for improvements in wireless sensor networks [29]. Optimising energy usage is vital for sustainability and cost-effectiveness in smart cities. Examining existing data fusion mechanisms is essential for sustainability in building energy systems [67]. Effective data fusion can help reduce energy consumption and promote more sustainable urban development. Privacy and security-related issues in industrial infrastructure IoT-based systems must also be addressed to ensure the trustworthiness of smart city technologies [34]. Protecting sensitive data and ensuring the security of critical infrastructure are paramount.

Moreover, developing deep learning-based urban acoustic classification systems is necessary to enhance noise pollution control and urban quality of life [24]. Lastly, considering spatiotemporal fire data in Urban Fire Situation Forecasting algorithms is crucial for improving safety and emergency response in smart cities [22]. These algorithms can help predict and mitigate the impact of urban fires, reducing the risk to residents and property. In summary, these various research areas and priorities underscore the multifaceted nature of urban data analysis and its importance in building smarter and more sustainable cities.

6.1.3. Internet of Things (IoT) and data integration

The field of machine learning (ML) and artificial intelligence (AI) is

facing several crucial motivations and opportunities in various domains. Firstly, there is a growing demand [31] for implementing ML algorithms on diverse nodes, including end and edge devices and cloud platforms, particularly in IoT applications within smart cities. This necessitates the development of adaptive and resource-efficient algorithms that can cater to each node's unique constraints and requirements. In the industrial IoT sector, there is an urgent need [80] to integrate AI technologies to enhance data transmission efficiency seamlessly. This integration can lead to more intelligent decision-making processes and optimisation of industrial operations. Privacy remains a paramount concern [42] in IoT data streaming. As data continues to flow from numerous devices, preserving the confidentiality and security of this data is essential. Implementing robust encryption and privacy-preserving techniques is crucial to mitigate potential risks. Another significant motivation is generating synthetic data [60] based on real data using innovative techniques. This synthetic data generation is vital for augmenting datasets, improving model performance, and overcoming data scarcity issues in various applications. In the domain of the Internet of Drone Monitor Systems, there is a need [45] to advance real-time object segmentation, enabling drones to detect and track objects in real-world scenarios efficiently, which is essential for tasks like surveillance and monitoring.

Moreover, the field of social computing is evolving, requiring advancements in social knowledge representation and solutions for image fusion and ML [40]. These developments can enhance our ability to analyse and understand complex social interactions and multimedia content. Efficiency and speed are essential factors that demand efficient, lightweight ML models with high counting accuracy and fewer parameters [27]. This is crucial for resource-constrained environments and applications. Balancing prediction performance and computational efficiency is a persistent motivation [25] as ML models become more complex. Striking the right balance is critical to ensure practical and real-time applications. Multi-scale spatiotemporal information fusion [26] is another emerging area that seeks to integrate data from various sources and resolutions, providing a comprehensive understanding of dynamic environments. Finally, developing approaches to recognise outdoor places of interest in unfamiliar environments [64] is vital for smart cities, enabling residents and visitors to navigate and interact with their surroundings more effectively.

6.1.4. Transportation services and optimisation

Developing and enhancing urban transportation systems are critical for addressing the ever-growing motivations of congestion, pollution, and inefficient resource utilisation. In this context, several research areas and innovative approaches have emerged as essential components of the solution. As highlighted in [62], one notable endeavour focuses on efficiently allocating resources in ride-hailing services. This entails the optimisation of routes, driver assignments, and passenger pickups, aiming to reduce travel times, fuel consumption, and carbon emissions while improving service quality—the importance of accurate traffic speed prediction [30], highlighting the incorporation of spatiotemporal information. This approach can provide more precise forecasts by considering road conditions, weather, and historical data, enabling better traffic management and congestion mitigation strategies.

Furthermore, the concept of intelligent transport and parking services, as denoted in reference [63], is gaining traction. These services leverage advanced technologies like IoT sensors, data analytics, and AI algorithms to optimise parking availability and streamline transportation logistics, ultimately reducing urban congestion and emissions. Integrating data from various sources [69], such as GPS, lidar, and cameras, enhances navigation systems' accuracy, enabling safer and more efficient travel. This approach is instrumental in developing autonomous vehicles and intelligent transportation systems.

Lastly, [32] highlights the need to motivate classical centralised paradigms to lower data communication costs. As the volume of data generated by transportation systems grows, adopting decentralised and

edge computing solutions can reduce the burden on central servers, improve data processing efficiency, and lower operational costs, ultimately contributing to more sustainable and responsive transportation networks. In conclusion, these research areas and approaches collectively represent a multifaceted strategy for addressing urban transportation motivations, aiming to create smarter, more efficient, and sustainable cities.

6.2. Challenges

Smart cities face challenges in implementing information fusion, including data integration from various sources, privacy and security concerns, and quality and dependability issues (see Fig. 9).

6.2.1. Data extraction and security challenges

Information extraction from bridge inspection reports regarding the condition of bridge elements is a formidable task due to the presence of multiple, vague, uncertain, and often conflicting pieces of information about the state of these elements. Such complexities can significantly hinder the effectiveness of data-driven approaches aimed at predicting bridge deterioration because they can undermine the generalizability and separability of the predictive models [35]. Furthermore, collecting, cleansing, curating, and maintaining urban data from various heterogeneous sources is an intricate and labour-intensive manual endeavour [23]. This complexity is compounded when dealing with higher-order and higher-dimensional heterogeneous big data, which poses challenges in their representation and fusion. These challenges must be addressed alongside computational complexity, robustness, and security concerns, highlighting the multifaceted nature of effectively managing and utilising urban data [33]. Current intrusion detection schemes that safeguard mobile cloud environments encompassing various client networks face significant challenges. One major issue lies in their reduced effectiveness, primarily due to the high computational complexity of monitoring and analysing diverse network traffic patterns. These schemes often need help to keep pace with the rapidly evolving threat landscape, necessitating frequent rule updates, which can be resource-intensive and time-consuming [65].

In the realm of medical IoT, security and privacy threats are of paramount concern. Achieving the delicate balance between enhancing security measures and maintaining model accuracy is a complex challenge. Medical IoT devices are vulnerable targets for cyberattacks, as compromising their security could severely affect patient safety and data privacy. Striking the proper equilibrium between robust security protocols and the seamless operation of medical IoT systems remains a critical endeavour [48]. Furthermore, the security of current healthcare systems during the acquisition and analysis of sensitive patient data needs to be improved. System failures, whether caused by technical glitches or intentional attacks, can pose significant risks to the confidentiality and integrity of patient information. The healthcare industry should invest in building resilient infrastructure and implementing robust security measures to mitigate these potential vulnerabilities [49].

Privacy risks can occur in IoT frameworks during communication between local devices and untrusted edge servers. These risks may result from inadequate encryption, insecure data transmission protocols, or unauthorised access attempts. To protect user privacy in IoT ecosystems, we must develop and adopt robust security mechanisms that safeguard data as it travels from edge devices to servers. This will help to minimise the possibility of privacy breaches [42].

6.2.2. Computational challenges

Energy consumption and latency pose significant challenges in wireless sensor networks, primarily attributable to the substantial volume of heterogeneous data these networks handle, coupled with the inherent energy constraints of sensor nodes [29]. In traffic management, using extensive sensor and road data is a computational endeavour fraught with complexity, often pushing the limits of current approaches, which can only concurrently manage a restricted number of roads [50]. Moreover, prevailing methods in this domain tend to neglect non-Euclidean inner correlations or heavily depend on external information, hampered by their models' limited transferability and extensibility [53]. Regarding resource allocation in heterogeneous industrial IoTs, many deep reinforcement learning-based algorithms exhibit feature extraction, scalability, and generalisation constraints, posing substantial limitations [80]. Furthermore, within human emotion classification, current machine learning algorithms grapple with accommodating the diverse range of multi-modal information originating from sensors and features. This often necessitates feature engineering, which can inadvertently compromise the accuracy and reliability of the models [39]. These challenges highlight the pressing need for innovative solutions and advancements in various domains, from wireless sensor networks to traffic management and machine learning, to overcome these limitations and drive progress in the field.

6.2.3. Transportation challenges

As stated in [55], autonomous vehicles rely on information gathered from various heterogeneous sensors to navigate safely and effectively. This multi-sensor approach is crucial because, as highlighted in [56], depending solely on a single sensor or data source for navigation can be exceptionally challenging and may lead to safety risks. Furthermore, autonomous vehicles face complex decision-making scenarios, particularly in lane-changing situations, as emphasised in [57]. These challenges underscore the need for advanced algorithms and sensor fusion techniques to ensure safe and efficient navigation. In the context of smart cities, [54] mentions the importance of region-based traffic and electricity flow prediction, leveraging historical external information. This approach is vital for optimising resource allocation and enhancing the overall efficiency of urban systems. In wireless sensor networks (WSNs), as discussed in [32], extracting meaningful information from heterogeneous big data is a significant challenge, particularly in automatically detecting features in anomalous systems. This highlights the need for robust data analytics and anomaly detection techniques in WSN applications. As noted in [61], traffic flow prediction often needs to improve accuracy by only considering regional information or situational graph representations, neglecting external factors and complex spatiotemporal relationships, as [62] points out. Improved prediction methods should encompass these elements for more effective online ride-hailing system decisions. The issue of traffic state, as mentioned in [30], needs to be investigated and mainly influenced by anomalies and spatiotemporal aspects. Addressing this challenge is essential for enhancing traffic management and reducing congestion in urban areas. As highlighted in [51], bike-sharing services face demand uncertainty and manual rebalancing issues, resulting in a lack of available station docks and bikes. These challenges require innovative solutions to optimise bike-sharing operations. As discussed in [63], parking services in smart cities need to be improved by traffic flow constraints, leading to time and fuel wastage. Improving parking management systems is crucial for reducing congestion and environmental impacts. Lastly, [64]

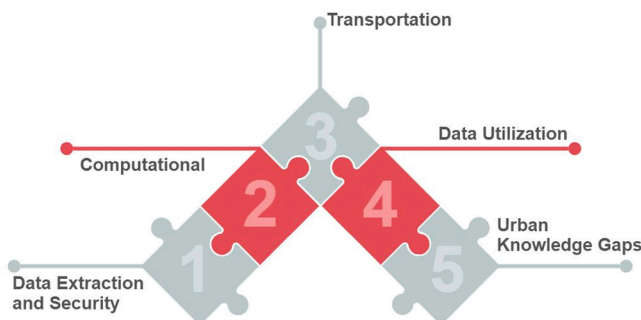


Fig. 9. Challenges diagram.

underscores the importance of recognising unfamiliar places of interest for enhancing user experience and navigation in smart city environments. This highlights the need for advanced location-based services and recommendation systems.

6.2.4. Data utilisation challenges

The integration and analysis of vast transportation data from homogeneous and heterogeneous sensors present a formidable challenge [36]. Similarly, crowd counting encounters a significant hurdle in scale variation, necessitating intricate network structures that demand impractical computational resources, particularly in edge devices [27]. The quest for enhanced building energy efficiency grapples with the elusive search for appropriate information fusion mechanisms [40]. Anomaly detection in extensive video datasets confronts a multitude of issues, including computational complexity, false positives due to networks primarily being trained on normal events, a shortage of annotated abnormal events, subpar quality of outdoor sensor data, and a wide range of image classes [41]. Moreover, the development of data-driven cities faces a fundamental limitation in insufficient training data [60]. In the realm of smart cities, classifying urban acoustics is a complex task due to the diversity, spontaneity, and intricacy of noise sources [24]. Furthermore, addressing challenges related to computational efficiency, intricate fusion of heterogeneous data sources, and managing uncertainties and missing information is an ongoing struggle in various domains [25]. These challenges underscore the need for innovative solutions and interdisciplinary collaboration to harness the full potential of data-driven technologies in addressing urban and transportation-related issues while ensuring scalability and practicality.

6.2.5. Urban knowledge gaps

The limited literature on Cyber-Physical Systems-based intelligent disaster prevention and mitigation structural systems [43] underscores the pressing need for more research in this critical area. With the increasing frequency and severity of natural disasters, harnessing the power of Cyber-Physical Systems to create intelligent infrastructure capable of predicting, preventing, and mitigating disasters is paramount. The limited literature signals an opportunity for researchers and engineers to explore innovative solutions that can better protect communities and save lives in the face of calamities. Similarly, the limited literature on traffic management systems in urban roads [68] highlights an ongoing challenge for urban planners and transportation experts. As cities continue to grow, the strain on transportation networks intensifies, making effective traffic management crucial for reducing congestion emissions and improving overall urban livability. More research is needed to explore advanced technologies and strategies to optimise traffic flow, reduce commute times, and enhance urban mobility. The scarcity of literature on insights and the purpose of mobile intelligent actors in social computing for smart cities [40] points to a burgeoning field that has yet to be fully explored. Mobile intelligent actors have the potential to revolutionise how we interact with and navigate smart cities, but their role and impact still need to be better understood. Further research in this area can shed light on how these actors can enhance social interactions, efficiency, and the overall quality of life in modern urban environments. These three areas of limited literature underscore the critical need for continued research and innovation in smart cities and urban development.

These sections and subsections provide a structured overview of the challenges across various domains, making it easier to understand the specific issues in each area.

6.3. Recommendations

Smart cities require robust data infrastructure, advanced analytics, encryption, and cooperation for efficient information fusion, with regular surveillance and evaluation crucial for ongoing optimisation and improvement (see Fig. 10).

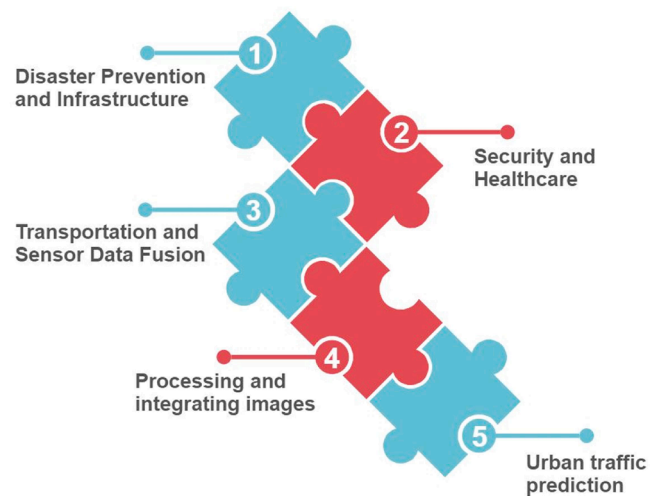


Fig. 10. Recommendations Diagram.

6.3.1. Disaster prevention and infrastructure

The proposed fusion method aims to enhance the prediction of bridge deterioration through machine learning techniques. This method will be refined to incorporate diverse types of bridge data, enabling more informed maintenance decision-making. Furthermore, the refinement process will address complex cases, focusing on conflict resolution and pattern preservation, ensuring the accuracy and reliability of the prediction model [35]. In the context of future cyber-physical system (CPS)-based disaster prevention with Building Information modelling (BIM), it is recommended to emphasise practical case studies that emphasise integration and utilise stable, credible, real-time, and secure network communication technology. The authors propose implementing a visual cyber-physical system for disaster prevention and mitigation, leveraging the power of BIM. The system would incorporate screens displaying geographic location, information, and images, facilitating effective decision-making and response coordination [43].

6.3.2. Security and healthcare

The machine learning-based intrusion detection scheme presented in the study offers a valuable solution for ensuring communication security in mobile cloud computing environments. This scheme effectively safeguards the integrity and confidentiality of client networks and mobile cloud infrastructure by protecting against DDoS and MITM attacks and securing virtual machines through a cloud-of-cloud model [65]. In the context of Healthcare 5.0, the paper recommends integrating blockchain technology with federated learning for secure health monitoring. This integration enables physicians to effectively monitor patients and predict diseases using real-time streaming data-driven event detection and localisation mechanism (RTS-DELM)-enabled systems. By incorporating the proposed approach, healthcare professionals can enhance the security and privacy of health-related data while leveraging federated learning for improved predictive capabilities [48].

To reconcile diverging pictures derived from heterogeneous sources, the study suggests using supervised machine learning techniques in order to harmonise different perspectives of smart cities. Additionally, it is recommended to preprocess and transform diverse datasets with different spatio-temporal characterisations to make them comparable. Adopting this approach makes generating a unified and comprehensive understanding of smart cities possible, enabling effective decision-making and urban planning [23]. Furthermore, the authors propose testing their approach on diverse datasets with increased participants, modalities, and factors such as pollution and crowd density. They also suggest exploring the application of deep learning techniques to large physiological datasets to gain new insights and further advance the field [39]. The authors recommend employing cascaded supervision training

and assembling intermediate predictions to achieve high-quality results in image reconstruction. This approach enhances the accuracy and fidelity of image reconstruction processes, contributing to improved visual outcomes in various applications [46].

6.3.3. Transportation and sensor data fusion

To enhance clustering efficiency and accuracy, the study proposes the utilisation of IT-FCM (Information Technology-based Fuzzy C-Means) with smart data derived from significant data sources, including multi-modal smart city data. Incorporating smart data into the clustering process enables more efficient and accurate clustering outcomes. Additionally, edge-cloud co-clustering enhances clustering efficiency, enabling more effective data analysis and decision-making in smart city contexts [37]. The study highlights the benefits of explainable recommender systems, which provide intuitive explanations for energy-saving actions, thereby improving user acceptance rates. These systems can offer explanations either post-hoc or promptly based on data fusion analysis, facilitating personalised recommendations to end-users and promoting energy conservation practices. These systems reduce energy wastage and contribute to sustainability and efficiency in various domains [67].

The context of Industrial Internet of Things (IIoT) settings, the authors propose adopting dual-attention deep reinforcement learning, lifelong learning, and multi-granularity fusion techniques. These approaches enhance resource utilisation, system performance, and accuracy in IIoT environments. By leveraging these advanced techniques, the efficiency and effectiveness of IIoT systems can be significantly improved [38]. Emphasising the importance of updating information from Roadside Units (RSUs) to reduce navigation errors, the study recommends utilising a random forest model to determine RSU responsiveness. Navigation accuracy can be improved by ensuring timely and accurate information exchange between vehicles and RSUs, contributing to safer and more efficient transportation systems [55].

The paper proposes the use of stacking spectra spectrograms to analyse time-frequency energy variations in acoustic signals. To facilitate Urban Acoustic Classification (UAC) analysis, the paper suggests using feature extractors, such as ResNet152 and Inception-ResNet-v2. These techniques can help obtain a more comprehensive understanding of urban soundscapes, enabling effective monitoring and management of acoustic environments. Overall, this can help better manage urban noise pollution [24]. The study suggests the integration of AI-based sensor information fusion with comprehensive transportation data for deep supervised learning, aiming to enhance transportation models and advance the development of smarter cities. By incorporating diverse data sources, including sensor data, this approach enables more accurate and robust transportation modelling, improving urban planning and management [36].

6.3.4. Processing and integrating images

In terms of recognition tasks, the study suggests the effectiveness of employing location-based filtering and global descriptor similarity-based ranking techniques to enhance recognition results. These approaches offer valuable improvements over the time-consuming and less effective local descriptor-based re-ranking methods. By leveraging location-based filtering and global descriptor similarity, recognition performance can be significantly enhanced, leading to more accurate and efficient recognition systems [64]. The authors underscore the significance of considering spatial-temporal correlations among multiple local regions within a city to achieve accurate prediction outcomes. By incorporating these correlations into predictive models, a more comprehensive understanding of urban dynamics can be obtained, improving prediction accuracy and reliability [54].

6.3.5. Urban traffic prediction

For smart traffic management, the study suggests the utilisation of fog devices and vehicle cameras to detect and report traffic violations

effectively. By leveraging these technologies, traffic management systems can enhance their ability to identify and address infractions, contributing to improved road safety and traffic flow [59]. The recommendation is integrating BSN—Cloud (Body Sensor Network-Cloud) for efficient human activity recognition and monitoring within mobility contexts. This integration involves leveraging high-profile devices to handle computing-intensive applications. Cloud computing is proposed as a suitable solution for managing distributed data and enhancing complex event processing, real-time processing, massive scale capabilities, and data fusion approaches, thereby enabling robust and effective monitoring systems [44].

In order to improve the efficiency of wireless sensor networks, neighbourhood-based approaches for decentralised anomaly detection are recommended. This can be achieved by evaluating the spatio-temporal correlation and the influence of neighbourhood size on performance. By doing so, wireless sensor networks can enhance their anomaly detection capabilities, resulting in more efficient and dependable operations [32]. The proposed method holds promise for multiple-traffic data collection and sensor network design. Future research could improve accuracy and robustness, particularly for large vehicles, to enhance its applicability.

Additionally, exploring more complex scenarios and incorporating three or more nodes for vehicle-type recognition would contribute to the method's versatility and reliability [58]. To study human mobility behaviour in smart cities, the authors suggest the utilisation of agent-based simulations and reinforcement learning to generate synthetic data. However, they emphasise the need for validation and integration with real-world data to ensure the accuracy and applicability of the generated synthetic data. Combining synthetic and real-world data can provide a more comprehensive understanding of human mobility patterns, facilitating effective urban planning and resource allocation [60]. For optimisation purposes, the paper recommends adopting a discretise-then-optimize approach to improve accuracy and efficiency. The authors also suggest considering intrinsic and extrinsic factors and utilising separate neural networks to avoid brute-force computations. Furthermore, they recommend further research on sudden changes and hysteresis to enhance optimisation [25].

The paper proposes improving traffic management strategies by incorporating accident spatiotemporal features and introducing an attention mechanism in the context of road networks. This can be achieved by integrating and categorising congestion effects, enhancing the semantic expressiveness of road networks and leading to a more comprehensive understanding of traffic dynamics [30]. To improve operational efficiency and public information sharing in vehicular ad hoc networks (VANETs), it is recommended to use low-latency communication. Furthermore, applying machine learning algorithms for VANET data analysis can address safety, communication, and traffic issues. By leveraging low-latency communication and machine learning techniques, VANETs can perform better and contribute to safer and more efficient transportation systems [63].

6.4. Limitations of information fusion in smart cities

Information fusion is pivotal in augmenting decision-making accuracy, facilitating anomaly detection, and enabling future event prediction by integrating data from diverse sources. However, it is essential to acknowledge the presence of certain limitations within this domain. These limitations include input data quality, computational costs, and the selection of appropriate algorithms. Addressing these limitations is essential to enhance the effectiveness and reliability of information fusion methodologies.

Information fusion serves as a paramount objective to enhance the quality of information by integrating data from various sources, thereby aiming to improve decision-making accuracy, facilitate anomaly detection, and enable future event prediction. Nevertheless, the practice of information fusion is not without its limitations, as delineated in

Table 1
Information fusion limitations in smart cities.

Ref.	Limitations
[35]	<ul style="list-style-type: none"> Struggling with missing or incomplete data may affect fused data's accuracy. The method used may not be adaptable to different types of bridges. It has an entropy-based evaluation shortcoming regarding ML-based bridge deterioration prediction.
[65]	<ul style="list-style-type: none"> Incomplete or irregular data collection could influence the accuracy of the method. Various mobile cloud environments with diverse network designs may produce different consequences due to needing to be more generalisable. The importance of accurately differentiating malicious activities from normal network behaviour is not assessed regarding false positives and negatives.
[48]	<ul style="list-style-type: none"> Integrating blockchain technology and federated learning can be computationally expensive. Training the model over multiple nodes increases the network latency.
[66]	<ul style="list-style-type: none"> Lack of generalizability due to the small sample size used in the method assessment. Lack of a more efficient feature extraction method able to drive emotion representation. Different scales of multimodality may guide feature-level fusion to constructing irrelevant features, hence model overfitting.
[33]	<ul style="list-style-type: none"> Lack of evaluation based on other fusion methods.
[37]	<ul style="list-style-type: none"> Ignore the impact of noise on the data fusion process. The fusion process may be unable to keep up with high-speed data streams. The fusion process is sensitive to noise in the data.
[29]	<ul style="list-style-type: none"> It does not consider the changes in the traffic conditions. It is difficult to handle different types of data from the WSNs. Stealing data is accessible in this process.
[41]	<ul style="list-style-type: none"> The fusion process is a simple weighted sum of the features from the two streams. An imbalance in informative spatial and temporal features leads to a loss of model adaptivity.
[43]	<ul style="list-style-type: none"> Absence of integration and interoperability between various data sources and systems.
[23]	<ul style="list-style-type: none"> Ignore the temporal dimension when merging the data. Ignore the quality of the data.
[50]	<ul style="list-style-type: none"> A low-weighted feature assigned through graph convolution operation is ignored, leading to suboptimal predictions. The fixed averaging weights during training make the process not adaptive to changes in the traffic pattern or the road network.
[44]	<ul style="list-style-type: none"> When the sensors cannot see the user, the Kalman filter can no longer accurately estimate the user's activity (causing occlusions)
[27]	<ul style="list-style-type: none"> When the images lack resolution, the model does not effectively work.
[67]	<ul style="list-style-type: none"> Complexity
[39]	<ul style="list-style-type: none"> The method is restricted to a specific type of data They are not evaluated under large-scale data. The fusion process is computationally expensive devices with limited resources.
[51]	<ul style="list-style-type: none"> The fusion process did not consider the latency. Collaborative computing algorithm is sensitive to noise.
[31]	<ul style="list-style-type: none"> The Bayesian process is sensitive to prior distribution and computationally expensive for posterior distribution.
[52]	<ul style="list-style-type: none"> The fusion process is sensitive to noise and outliers. The weighted majority voting rule is computed based on the accuracy of each sensor; incorrect sensor reads lead to wrong results.
[68]	<ul style="list-style-type: none"> The fusion process is computationally expensive. Due to latency, it may accurately reflect error data.
[34]	<ul style="list-style-type: none"> Blockchain federated learning is a complicated and computationally expensive operation.
[53]	<ul style="list-style-type: none"> Lack of data required for training. The fusion method is computationally expensive.
[45]	<ul style="list-style-type: none"> The authors used majority voting as a final prediction, ignoring the issue of the prediction's confidence.
[40]	<ul style="list-style-type: none"> The fusion method is not robust to noise and outliers.
[80]	<ul style="list-style-type: none"> The federated meta-learning-based knowledge fusion process requires training a meta-learner on the knowledge of the DADR algorithms. This process can be computationally expensive, especially for large datasets. The reinforcement learning-based knowledge transfer process also requires training a reinforcement learning agent. This process can also be computationally expensive, especially for complex environments.
[54]	<ul style="list-style-type: none"> The LMST3D-ResNet fusion process is computationally expensive. It cannot capture long-range dependency.
[55]	<ul style="list-style-type: none"> The fusion method is susceptible to data training noise and computationally expensive.
[69]	<ul style="list-style-type: none"> The proposed method is not implementable for real-time processing.

Table 1 (continued)

Ref.	Limitations
[57]	<ul style="list-style-type: none"> It requires fusing the information from many neighbouring vehicles; this makes it difficult to determine the optimal weights for the data from the adjacent cars.
[58]	<ul style="list-style-type: none"> It has a high sensitivity to the weights assigned to the data from the sensors. Noisy data from the sensors affect negatively the fusion process.
[46]	<ul style="list-style-type: none"> Due to the upsampling requirement of the features from different layers of the CNN, it is computationally expensive. The fusion process is sensitive to the choice of weights.
[24]	<ul style="list-style-type: none"> Correlated features extracted by CNN can be correlated, leading to model overfitting. Moreover, the fusion process can be computationally expensive.
[25]	<ul style="list-style-type: none"> The fusion process is computationally expensive and may only be suitable for some urban flow prediction problems.

Table 1. Accordingly, these limitations were categorised into multiple related groups based on the significance of each topic in the context of information fusion:

6.4.1. Missing data and fusion accuracy issues

Research projects have drawn attention to the issue of missing data, which pertains to the absence or unavailability of specific data points or features within a dataset. Multiple studies have shed light on the potential ramifications associated with the presence of missing or incomplete data on the accuracy of fused data [35]. Moreover, the method's accuracy can be influenced by the collection of data that needs to be completed or characterised by irregularities [65]. A notable concern pertains to the impact of noise on the data fusion process, an aspect that has been observed to be disregarded in specific research endeavours [33]. Additionally, it has come to attention that the fusion process exhibits sensitivity to noise in the data, thereby introducing the possibility of distortions in the resulting outcomes [37]. Compounded by latency issues, the fusion process may inadvertently incorporate error data, compromising its reliability [68]. Lastly, empirical evidence supports the assertion that including noisy data emanating from sensors can adversely impact the overall quality of the fusion process [58].

6.4.2. Adaptability and generalisability issues

Recent studies have focused on adaptability and generalizability, which refer to a method's ability to function effectively in various scenarios, datasets, or circumstances. Recent studies have brought forth several noteworthy considerations. Firstly, one limitation identified is the adaptability of the employed method to different types of bridges [35]. Moreover, utilising diverse network designs within various mobile cloud environments can yield disparate outcomes, underscoring the need for enhanced generalizability [65]. Furthermore, the small sample size used in the method assessment has been recognised as contributing to its limited generalizability [66]. Additionally, the fusion process, which involves a straightforward weighted sum of features from two streams, may encounter imbalances in informative spatial and temporal features, leading to a loss of model adaptivity [41]. Adopting fixed averaging weights during training renders the process insensitive to changes in traffic patterns or road networks [50].

Moreover, the method is constrained in its applicability to a specific type of data [67]. More availability of training data poses a challenge, impeding the method's robustness [53]. The authors' reliance on majority voting as a final prediction fails to account for the confidence associated with the predictions [45]. Furthermore, the fusion method is susceptible to noise and outliers, compromising its robustness [40]. The proposed approach is unsuitable for real-time processing, presenting implementation challenges [69]. Additionally, the weights assigned to sensor data exhibit high sensitivity, significantly influencing overall performance [58]. Lastly, the applicability of the fusion process may only extend universally to some types of urban flow prediction problems and is accompanied by substantial computational expenses [25].

6.4.3. Scalability, integration, and interoperability issues

Information fusion faces challenges in integration, interoperability, and scalability, as it requires combining diverse data from different sources, requiring common standards and protocols, and increasing data volume and variety. Several research findings have shed light on pertinent issues. Firstly, the absence of integration and interoperability among diverse data sources and systems has emerged as a significant concern [43]. Moreover, specific fusion processes have overlooked the consideration of latency, potentially impacting the timeliness of results [51]. Additionally, it has been recognised that the fusion process can impose substantial computational demands, posing challenges regarding computational resources and efficiency [68]. The adoption of blockchain federated learning has been acknowledged as a complex and computationally expensive operation [34].

Similarly, the fusion method itself has been identified as computationally burdensome [53]. Furthermore, the vulnerability of the fusion method to noise in data training and its associated computational costs have been highlighted [55]. Additionally, the extraction of correlated features by CNN can lead to issues of model overfitting, and the subsequent fusion process may entail additional computational expenses [24]. These findings underscore the imperative to address integration and interoperability challenges, consider latency implications, optimise computational efficiency, and mitigate concerns related to noise and overfitting. Doing so will enhance the effectiveness and practical feasibility of fusion methods.

6.4.4. Specific factors and dimension issues

Information fusion has limitations, particularly in data quality and availability, and its application may be limited by computational complexity and resource requirements, particularly in real-time or resource-constrained contexts, affecting its effectiveness. Multiple research studies have shed light on notable limitations within information fusion. Firstly, an identified study pinpointed a shortfall in entropy-based evaluation concerning machine learning-based bridge deterioration prediction, suggesting a potential inadequacy in assessing uncertainty and variability [35]. Moreover, specific fusion approaches were observed to overlook the temporal dimension during data integration, potentially disregarding crucial temporal patterns and dynamics. The same study emphasised the essentiality of considering data quality in the fusion process, as neglecting it may introduce inaccuracies and errors to the fused outcomes [23].

Furthermore, the study highlighted the challenges the Kalman filter faces, employed for user activity estimation, in circumstances where sensors fail to perceive the user, leading to inaccuracies due to occlusions [44]. Similarly, insufficient image resolution hindered model effectiveness, underscoring the necessity for higher-quality images to enhance fusion outcomes [27]. Lastly, the study underscored the fusion method's inability to capture long-range dependencies, which restricts its capacity to model and incorporate relationships and influences effectively over extended periods [54]. These findings underscore the importance of addressing evaluation methodologies, integrating temporal considerations, ensuring data quality, managing occlusion challenges, enhancing image resolution, and capturing long-range dependencies to augment the effectiveness and reliability of information fusion techniques.

6.4.5. Privacy and security issues

Information fusion raises security and privacy concerns, requiring the resolution of potential risks and vulnerabilities, including safeguarding sensitive data and preventing illegal access or breaches. Several research studies have highlighted essential findings concerning security and accuracy in information fusion. Firstly, a study identified the accessibility of data theft within this process, indicating potential vulnerabilities that malicious actors could exploit. This underlines the importance of implementing robust security measures to safeguard sensitive data and prevent unauthorised access [29]. Additionally,

another study examined the weighted majority voting rule utilised in information fusion, revealing that the accuracy of each sensor influences the computation of this rule.

Consequently, incorrect readings from sensors can result in erroneous outcomes. This emphasises the need to ensure the accuracy and reliability of sensor data to maintain the integrity of the fusion process and mitigate the risk of producing incorrect results [52]. These findings underscore the significance of implementing stringent security measures to protect against data theft and ensuring the accuracy of sensor readings to enhance the reliability and trustworthiness of the information fusion process.

7. Analysis of characteristics and research gaps

In this section, attention is directed towards identifying gaps in future research pertaining to information fusion in the context of smart cities, specifically highlighting areas currently underrepresented in the existing literature. The current state-of-the-art in smart cities is delineated through tables and detailed analyses, thereby underscoring the imperative for additional exploration and comprehension of this pivotal aspect. By illuminating these gaps, a foundation is laid for future investigations that can contribute to advancing a holistic understanding of information fusion within smart cities.

7.1. Implementing trustworthy AI requirements in smart city information fusion

The prominence of transparency in AI-based solutions has garnered significant attention, primarily due to their reliance on historical and human-generated data, often resulting in opaque systems. This reliance raises ethical concerns regarding the implications of such data sources. In MedTech, the utilisation of AI-based solutions is increasingly recognised as pivotal, as they can foster justice, ethics, openness, and dependability. A framework comprising seven key components has been established to promote the development of trustworthy AI systems, encompassing human agency, technical robustness, privacy, data governance, transparency, diversity, non-discrimination, societal and environmental well-being, and accountability.

Within the context of smart city applications, the authors underscore the significance of integrating trustworthy AI to ensure reliability, safety, and ethical usage, considering its potential impact on information fusion within smart city systems. Table 1 presents the frequency of trustworthy AI requirements in existing smart city literature to provide a comprehensive overview, highlighting the most frequently cited requirements. Additionally, the European Union has outlined seven essential elements of trustworthy AI, as depicted in Fig. 11, further reinforcing the importance of adhering to these principles in smart city contexts:

- 1. Human agency and oversight:** The inclusion of human agency and oversight represents critical components essential for upholding fundamental rights, integrating human decision-making processes, and emphasising the indispensable role of human supervision. These elements play a pivotal role in ensuring the protection of individual rights, fostering inclusivity, and maintaining a necessary level of human control within AI systems.
- 2. Technical robustness and safety:** This concept encompasses the system's capacity to withstand security threats, uphold accuracy, and ensure reliability despite potential system failures. This attribute underscores the importance of developing resilient, secure AI systems that can maintain their intended functionalities under adverse conditions.
- 3. Privacy and data governance:** The policy places significant importance on privacy and data governance, with a focus on maintaining data quality and integrity, upholding privacy rights, and facilitating appropriate data access. These measures aim to establish

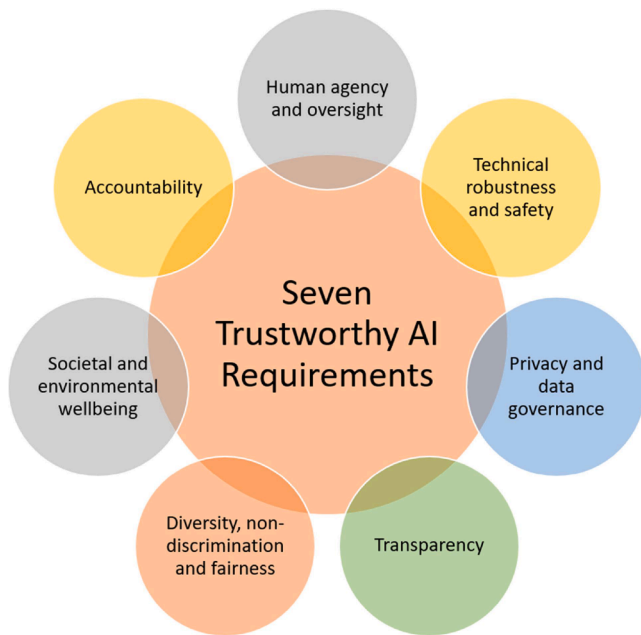


Fig. 11. The seven requirements of trustworthy AI [81].

robust frameworks safeguarding sensitive information, promoting responsible data handling practices, and enabling secure and lawful data utilisation.

4. **Transparency:** Transparency entails the tracing and elucidation of decision-making processes and the clear communication of outcomes to relevant stakeholders. This element emphasises the need for openness and comprehensibility in AI systems, ensuring the rationale behind decisions is traceable, understandable, and accountable. By promoting transparency, stakeholders can gain insights into the functioning of AI systems, fostering trust and facilitating informed decision-making.
5. **Diversity, non-discrimination, and fairness:** The policy emphasises diversity, non-discrimination, and fairness, focusing on ensuring accessibility, universal design, and stakeholder participation to mitigate the potential for unfair bias. This element underscores the importance of promoting inclusivity, equal treatment, and active engagement of diverse stakeholders. By fostering a culture of fairness and preventing discriminatory practices, the policy aims to create unbiased, equitable AI systems that represent all individuals' needs and perspectives.
6. **Societal and environmental well-being:** The concept of societal and environmental well-being encompasses considering sustainability, environmental impact, societal influence, and democratic processes. This element highlights the importance of assessing the broader implications of AI systems on the well-being of society and the environment. By incorporating sustainability measures, minimising environmental harm, and promoting democratic values, this concept seeks to ensure that AI applications contribute positively to the overall welfare of society and align with long-term societal and environmental goals.
7. **Accountability:** Accountability encompasses several key aspects, including auditability, mitigation of negative consequences, reporting mechanisms, trade-off considerations, and appropriate redress when necessary. This element underscores the importance of establishing mechanisms that enable the tracing and evaluating of AI system operations, addressing any adverse outcomes, and maintaining a balance between competing priorities. By ensuring accountability, stakeholders can have confidence in the responsible and ethical deployment of AI systems, with the ability to hold relevant parties accountable for their actions and decisions.

The implementation and continuous evaluation of the seven essential needs of trustworthy AI are crucial throughout the entire lifespan of an AI system, considering contextual factors and potential conflicts. These criteria should be tailored to the specific application and encompass all AI systems that directly or indirectly impact individuals while acknowledging that certain domains, such as industrial settings, may have varying relevance. Some of these needs may already be addressed by existing legislation [82]. AI practitioners are responsible for fulfilling their legal obligations in terms of universally applicable norms and regulations specific to their respective domains, in accordance with the first component of trustworthy AI.

Furthermore, the authors emphasise the significance of integrating "trustworthy AI" principles within smart city applications to ensure reliability, safety, and ethical utilisation. Through a comprehensive analysis of pertinent publications in this field, they have identified the most frequently referenced requirements for trustworthy AI, underscoring the potential influence of AI on information fusion outcomes. A summary of the frequency of trustworthy AI requirements in smart city literature can be found in Table 2.

Table 2 analyses the frequency of trustworthy AI requirements in the literature on smart cities. Each requirement is categorised as very low (VL), low (L), medium (M), high (H), or very high (VH) based on its prevalence across the references. The table offers a comprehensive examination and discussion of each requirement, providing valuable insights into the critical considerations for trustworthy AI in the context of smart cities. It serves as a concise and informative resource for researchers, policymakers, and practitioners seeking to understand and implement trustworthy AI principles in smart city initiatives:

1. Based on the surveyed literature on information fusion for smart cities, it is evident that all the studies emphasise the necessity of 100 % human oversight and agency. The distribution of percentages across the categories of VH (0 %), H (0 %), M (0 %), L (0 %), and VL (100 %) indicates that no study reported fully autonomous systems operating without human input or oversight. This finding underscores the prevalent requirement for some level of human control in all the systems examined. This reliance on human involvement may stem from various factors, including the nascent field stage, ethical considerations, technical constraints, or safety considerations. However, it is essential to note that this statement is confined to the literature surveyed and may not reflect the entirety of the field. As technology progresses and further research is conducted, the extent of human agency and oversight necessary in these systems may evolve and change.
2. The study examines the aspect of technical robustness and safety across different categories, such as VH (2 %), H (12 %), M (76 %), L (2 %), and VL (8 %). The majority of the studies assign medium importance to this requirement. However, only a small percentage, 2 %, of the studies perceive technical robustness and safety as very high or very low in importance, while 12 % consider it to be of high importance, and 8 % regard it as very low importance. These findings suggest that, overall, information fusion for smart cities exhibits a satisfactory level of technical robustness and safety. However, a limited number of studies perceive this aspect as critical or high-risk, indicating that further attention and consideration may be warranted in assessing and mitigating potential risks associated with technical robustness and safety in smart city applications.
3. Analysing information fusion systems for smart cities reveals that privacy and data governance receive relatively low priority. Only 2 % of the studies acknowledge this requirement as high or low, 14 % as medium, and a significant majority of 82 % as very low. These findings suggest that the examined systems exhibit inadequate measures for robust privacy protection and data governance. Consequently, there is a potential lack of emphasis on safeguarding user data and ensuring compliance with data privacy regulations. This situation raises concerns, particularly for organisations that

Table 2
Smart city literature frequency of trustworthy AI requirements.

No.	Ref.	C1	C2	C3	C4	C5	C6	C7
1	[71]	VL	M	M	VL	VL	VL	VL
2	[72]	VL	M	VL	M	VL	VL	VL
3	[65]	VL	M	VL	VL	VL	VL	VL
4	[48]	VL	VH	M	VL	VL	VL	VL
5	[66]	VL	M	VL	VL	VL	VL	VL
6	[4]	VL	M	VL	L	VL	VL	VL
7	[33]	VL	M	L	VL	VL	M	VL
8	[36]	VL	M	VL	VL	VL	VL	VL
9	[37]	VL	M	VL	VL	VL	VL	VL
10	[41]	VL	M	VL	VL	VL	VL	VL
11	[43]	VL	L	VL	M	VL	VL	VL
12	[23]	VL	M	VL	VL	M	VL	VL
13	[50]	VL	M	VL	VL	VL	VL	VL
14	[44]	VL	H	VL	VL	VL	VL	VL
15	[27]	VL	M	VL	VL	L	VL	VL
16	[67]	VL	H	M	VL	VL	VL	VL
17	[39]	VL	M	VL	VL	VL	VL	VL
18	[51]	VL	M	VL	VL	VL	VL	VL
19	[31]	VL	VL	VL	M	VL	VL	VL
20	[52]	VL	M	VL	VL	VL	VL	VL
21	[68]	VL	M	VL	VL	VL	VL	VL
22	[34]	VL	H	M	M	VL	VL	VL
23	[53]	VL	M	VL	VL	VL	VL	VL
24	[38]	VL	M	VL	M	VL	VL	VL
25	[74]	VL	M	M	VL	VL	M	VL
26	[49]	VL	M	VL	VL	VL	VL	VL
27	[45]	VL	M	VL	VL	VL	VL	VL
28	[75]	VL	M	VL	VL	VL	VL	VL
29	[40]	VL	VL	VL	VL	VL	M	VL
30	[28]	VL	M	VL	VL	VL	VL	VL
31	[54]	VL	M	VL	VL	VL	VL	VL
32	[55]	VL	VL	VL	M	VL	VL	VL
33	[56]	VL	M	VL	M	VL	VL	VL
34	[69]	VL	M	M	M	VL	VL	VL
35	[42]	VL	M	H	VL	VL	VL	M
36	[57]	VL	M	VL	M	VL	VL	VL
37	[58]	VL	H	VL	VL	VL	VL	VL
38	[77]	VL	M	VL	VL	VL	VL	VL
39	[70]	VL	M	VL	VL	VL	VL	VL
40	[59]	VL	M	VL	VL	VL	VL	VL
41	[32]	VL	VL	VL	M	VL	VL	VL
42	[60]	VL	M	M	VL	VL	VL	VL
43	[79]	VL	M	VL	M	VL	VL	VL
44	[24]	VL	H	VL	VL	VL	VL	VL
45	[22]	VL	M	VL	VL	VL	VL	VL
46	[25]	VL	M	VL	VL	VL	VL	M
47	[26]	VL	M	VL	VL	VL	VL	VL
48	[62]	VL	M	VL	VL	VL	VL	VL
49	[30]	VL	H	VL	VL	VL	VL	VL
50	[63]	VL	M	VL	VL	VL	VL	VL

C1 = Human agency and oversight, C2 = Technical robustness and safety, C3 = Privacy and data governance,

C4 = Transparency, C5 = Diversity, non-discrimination and fairness, C6 = Societal and environmental well-being, C7 = Accountability. L = Low, VL = Very Low, M = Medium, H = High, VH = Very High.

handle sensitive or confidential information. To address these risks, it may be necessary to incorporate additional measures related to privacy and data governance, augmenting the system’s existing capabilities. Such enhancements would mitigate potential privacy breaches and ensure adherence to data protection standards, which is of utmost importance for organisations involved in handling sensitive or confidential data.

- The analysis of transparency in smart cities systems reveals that the requirements categorised as VH and H are not adequately addressed. The majority, comprising 76 % of the requirements, fall under the VL category. Furthermore, 22 % of the studies consider transparency medium important, while only 2 % of the requirements are classified as L. These findings indicate that the information fusion system primarily focuses on ensuring transparency for low-risk requirements, possibly neglecting the need for robust transparency

measures in higher-risk scenarios. However, a comprehensive assessment of the effectiveness of these measures necessitates additional information regarding the specific requirements and their implementation. Further exploration and understanding of the system’s transparency practices are essential to ascertain its overall efficacy and identify potential areas for improvement.

- The analysis of information fusion systems for smart cities reveals that a low priority is placed on the requirement of "Diversity, non-discrimination, and fairness." None of the studies considered this requirement very high or high importance, while only 2 % attributed medium or low importance to it. The majority, accounting for 96 %, regarded it as very low importance. These findings suggest that the information fusion system may not sufficiently prioritise promoting diversity, equity, and inclusion in its outputs, nor does it adequately address the potential biases that may arise in its models against certain groups. This lack of emphasis on fairness and non-discrimination could raise concerns for organisations or individuals operating in fields where these considerations are of utmost importance. To address these concerns, additional measures are necessary to assess and mitigate potential biases in the system’s outputs. Furthermore, it may be beneficial to supplement the system’s capabilities with tools or processes that actively promote fairness and non-discrimination. By doing so, organisations can work towards creating more equitable and inclusive smart city systems.
- The evaluation of information fusion in the context of smart cities indicates that "social and environmental well-being" is accorded low priority. None of the studies considered this requirement very high, high, or low importance, while only 6 % attributed medium importance to it. The overwhelming majority of studies, comprising 94 %, regarded it as very low importance. These findings suggest that the information fusion system may not adequately prioritise considering the potential impacts of its outputs on society and the environment. There needs to be more emphasis on social and environmental well-being, which raises concerns, particularly for organisations or individuals engaged in sustainable development or social justice. Additional measures may be necessary to address these concerns to assess and mitigate any negative impacts arising from the system’s outputs. By incorporating such measures, organisations can better ensure that the information fusion system aligns with the goals of promoting social equity and environmental sustainability within smart city initiatives.
- The analysis of smart city systems reveals a relatively low ranking for the accountability requirement. A significant majority of studies, representing 96 %, consider it very low importance. None of the studies indicate high, high, or low importance, while only 4 % assign medium importance to this requirement. These findings suggest that smart city systems may not prioritise transparency and accountability in their processes and outputs, which could have implications for organisations and individuals operating in highly regulated industries. It is advisable to consider additional measures, such as implementing auditing or documentation processes, to enhance transparency and accountability. These measures can involve tracking the system’s inputs and outputs to ensure the decision-making processes are clear and accountable. By implementing such measures, smart city systems can bolster transparency, instil trust, and meet stakeholders’ expectations in regulated industries.

The existing literature on information fusion for smart cities exhibits a limited integration of trustworthy AI aspects, particularly concerning diversity, non-discrimination, and fairness. These dimensions should be more frequently addressed, especially compared to other dimensions in AI systems. Technical robustness and safety, human agency and oversight, and privacy and data governance emerge as the most frequently discussed dimensions of trustworthy AI, with numerous studies assigning them high or very high ratings. However, dimensions such as diversity, non-discrimination and fairness, societal and environmental

well-being, and accountability should be given more attention, with medium or low ratings in the surveyed literature.

It is important to note that the results presented in the table reflect the specific focus of the reviewed studies and should not be taken as definitive indicators of the overall importance or relevance of each dimension of trustworthy AI in the development of smart city systems. Instead, the table serves as a valuable starting point for gaining insights into the prevailing requirements and priorities associated with trustworthy AI in the realm of smart cities. Further analysis and contextual interpretation are necessary to understand the subject matter comprehensively.

In summary, the identified dimensions of trustworthy AI provide valuable guidance for developing smart city systems. However, it is imperative to continuously examine and address the less frequently mentioned dimensions, such as diversity, non-discrimination, fairness, societal and environmental well-being, and accountability, to ensure the ethical and responsible implementation of AI technologies in the context of smart cities.

7.2. The dataset utilized in information fusion for smart city

Information fusion is vital in facilitating the efficient management of urban resources within smart cities. To achieve this, it is essential to rely on high-quality and relevant datasets, as they form the foundation for generating accurate and meaningful results. The fusion of this information is critical for various purposes, including policy formulation, resource allocation, and decision-making processes. In order to effectively utilise the datasets, it is crucial to recognise their significance and ensure their dependability, completeness, and representativeness. By prioritising these factors, smart cities can harness the power of information fusion to optimise resource utilisation and enhance overall urban governance.

Table 3 comprehensively summarises diverse datasets across multiple domains, encompassing transportation, healthcare, urban data, environmental data, crime, emotion detection, and machine learning. It presents a wide array of data types and formats, ranging from datasets incorporating multi-modal emotion data (e.g., audio, visual, physiological signals) to annotated surveillance videos and numerical/visual data. Geospatial data is also included, providing valuable insights into movement patterns and transport trajectories. Medical and health-related datasets combine health data with speech signals or medical images, facilitating disease prediction and COVID-19 analysis. Moreover, the table covers datasets related to traffic, urban data, environmental data, and energy consumption, enabling analysis of transportation patterns, environmental impact, and energy usage.

Nevertheless, it is essential to acknowledge certain limitations. Some datasets need more detailed information, which may hinder a comprehensive understanding of their contents and potential applications. Additionally, the criteria used to classify datasets as "big data" could benefit from further clarification to ensure consistency and accuracy. Furthermore, specific access requirements for private datasets are not adequately specified, which could pose challenges for researchers seeking to utilise such data.

The table provides a valuable overview of diverse datasets, highlighting their relevance across various domains. However, there is room for improvement in enhancing its comprehensiveness and accessibility by addressing the mentioned limitations.

7.3. The data categories and the information fusion plan for smart cities

Smart cities use data integration to make informed decisions and promote sustainable development. This involves combining environmental, transportation, social, and infrastructural data to understand city operations and citizen well-being. By analysing data quality, interoperability, privacy, and scalability, cities can manage resources, improve quality of life, and gain holistic insights. The full potential of

these cities lies in their data fusion plan.

Smart cities have garnered significant attention in recent years within the research community, driven by the projection that 68 % of the world's population will reside in cities by 2050 [83]. Consequently, managing existing resources and infrastructure to provide sustainable living conditions for this growing urban population has become increasingly challenging. The emergence of the IoT, big data, data mining, and information fusion is gradually paving the way for the realisation of smart cities. Table 4 presents studies centred around smart city information fusion strategies and the corresponding data categories. This table encompasses 11 distinct data categories delineated in its contents. Each column within the table signifies a specific fusion data type, encompassing sensor data, geographic information, or even a combination of all data categories within a singular dataset.

The provided table offers a comprehensive overview of multiple datasets, each subjected to meticulous evaluation to determine the presence of 11 distinct data categories. These categories encompass diverse valuable information, including Sensor Data obtained from various sensors measuring parameters such as temperature, humidity, and motion. Geographic information encompasses spatial details relevant to individuals, locations, and objects, including latitude, longitude, and elevation. Time and date data capture temporal aspects related to events or observations. Event Data comprises information regarding accidents, crimes, and natural disasters. Demographic Data provides insights into population attributes such as age, gender, race, and income. Environmental Factors encompass data associated with the environment, including air quality, water quality, and weather conditions. Social Media or Citizen Engagement Data refers to information sourced from social media platforms or collected directly from citizens, encompassing content such as tweets, Facebook posts, and survey responses. The table also includes categories such as identifying data sources, collecting and preprocessing data, performing data fusion, and validating and verifying data. Researchers and analysts can effectively utilise this table as a valuable tool to identify datasets relevant to their research or analytical projects readily. For instance, a researcher interested in investigating the relationship between air quality and crime can efficiently locate datasets containing air quality measurements and crime-related data by referring to the table.

Additional valuable insights can be obtained from the table analysis. It becomes apparent that a significant proportion of the datasets feature sensor data, geographic information, and time and date data, highlighting the extensive collection and utilisation of these categories in various research and analytical domains. Including social media or citizen engagement data in four datasets indicates a rising interest in harnessing these sources for research and analysis. Conversely, only three datasets provide details on data fusion, implying that this field is still in its early stages of development and evolution.

In summary, this table is an invaluable resource, comprehensively depicting the data categories encompassed within multiple datasets. By leveraging this resource, researchers and analysts can quickly identify relevant and applicable datasets for their research or analytical endeavours. The table's utilisation facilitates efficient data selection, enabling professionals to focus on datasets that align with their objectives and requirements.

7.4. AI techniques and methods for information fusion in smart cities

Smart cities are leveraging the power of AI to handle and analyse large volumes of data from diverse sources such as social media platforms, sensors, and government systems effectively. By harnessing AI capabilities, smart cities aim to enhance urban management practices, optimise resource allocation strategies, and ultimately improve their residents' overall quality of life. Various AI techniques, including data fusion, anomaly detection, predictive analytics, and decision support systems, are employed to enable the development of intelligent systems tailored for sustainable urban environments. These systems are designed

Table 3
The smart city information fusion dataset.

Ref.	Name	Description	Size	Link	Input Type and Format	Lawfully Collected	Big Data	Public or Private
[65]	N/A CRAWDAD RICE/AD_HOC_CITY	Sample subset of user information from the cloud premises Traces of movements of the city busses in Seattle	Several weeks' worth of data for 1200 Buses spanning 5100 km ² region	CRAWDAD rice/ad_hoc_city IEEE DataPort (ieee-dataport.org)	.tar.gz	Yes	No Yes	Private Public
[48]	Parkinson's disease NSL-KDD	Parkinson's Disease Prediction Intrusion Detection	31 patients, 195 instances of speech signals 41 functions, 150k records	https://archive.ics.uci.edu/dataset/174/parkinsons https://www.unb.ca/ci/datasets/nsl.html	Numerical: .zip (.data and .names) .txt and .ARFF	Yes	No Yes	Public
[66]	AFEW RECOLA BAUM-1 EMOEEG CMU-MOSE1 WESAD	Multi-modal emotion datasets	330 46 31 8 1000 15	https://www.scopus.com/record/display.uri?eid=2-s2.0-84866094334&origin=inward https://ieeexplore.ieee.org/abstract/document/6553805 https://www.scopus.com/record/display.uri?eid=2-s2.0-85029943602&origin=inward https://ieeexplore.ieee.org/document/8081305 https://www.scopus.com/record/display.uri?eid=2-s2.0-85063076498&origin=inward https://dl.acm.org/doi/10.1145/3242969.3242985	Audio, visual Audio, visual, ECG, EDA Audio, visual EEG, EOG, EMG, ECG, EDA Text, visual, audio EDA, EMG, RESP, TEMP and ACC	Yes	Yes	Public
[33]	Hetrec2011-lastfm-2k	N/A	1,864,579 user, artist, label triplet instances	https://api.winnipegtransit.com/	Textual and Numerical: .dat	Yes	Yes	Public
[36]	Winnipeg Transit Open Data Web Service	Winnipeg transport locations and trajectories with trip information (e.g., temperature and road conditions) from multiple users	A year of trip information collected from anonymous users spanning Winnipeg	https://api.winnipegtransit.com/	Textual and Numerical .JSON	Yes	Yes	Public
[37]	N/A	Government's reports of Dalian city	6000 records fallen into 6 subsets 8000 records fallen into 8 subsets	N/A	N/A	Yes	N/A	Public
[29]	Simulated Data	Simulated WSN parameters	200 sensor nodes, with each source generating 4000 bits	N/A	Textual and Numerical	N/A	N/A	Private
[41]	UCF-Crime RWF-2000	Annotated Surveillance Videos Surveillance Clips	1900 surveillance videos containing 13 instances of crime 2000 short surveillance YouTube clips involving anomalous behaviours	https://ieeexplore.ieee.org/document/8578776 RWF-2000: an open large-scale video database for violence detection	Visual	No	Yes	Public
[23]	Dati Comune Milano CORINE land cover Lombardia open data Telecom Italia Big Data Challenge OpenStreetMap	Milano demographics, call phone records, land use classification and points of interest in the region	10 s 10 Ks 100 Ms 1 Ks 10 Ks	http://dati.comune.milano.it/ https://www.eea.europa.eu/publications/COR0-landcover http://www.eea.europa.eu/publications/COR0-landcover http://theodi.fbk.eu/openbigdata/ https://www.openstreetmap.org/#map=5/-28.153/133.275	Shapefile and Tabular	Yes	Yes	Public
[50]	OpenStreetMap NavInfo Traffic Data platform: Beijing, Shanghai, and Guangzhou	Traffic information of 3 Chinese cities: Road Network topology and speed data	1-month worth of information on 3900 roads across the 3 cities with 8928-time instances	https://www.openstreetmap.org/nitrafficindex.com	Shapefile Numerical	N/A	Yes	Public
[67]	GREEND PLAID WHITED	Electrical appliance usage patterns and power consumption in domestic buildings	6-month daily recordings of 6 electrical appliances and power footprints of 11 electrical appliances in domestic buildings.	refhub.elsevier.com/S1566-2535(20)30,315-8/sbref0237	Numerical	Yes	Yes	Public

(continued on next page)

Table 3 (continued)

Ref.	Name	Description	Size	Link	Input Type and Format	Lawfully Collected	Big Data	Public or Private
[39]	EnvBodySens	Nottingham female participants' heart rate, galvanic skin response, SGR, body temperature, movement, and environmental data	40 females	Towards unravelling the relationship between on-body, environmental and emotional data using sensor information fusion approach - ScienceDirect https://citibikenyc.com/sytem-data	Numerical and Visual	Yes	Yes	Public
[51]	Citi Bike New York N/A	Bike trip records (duration, start/stop time, station IDs) 5 years of NYC weather data (time, condition, temperature, wind speed, humidity, precipitation)	5.35 M records 5 years of hourly records	https://citibikenyc.com/sytem-data	N/A	Yes No	Yes	Public
[68]	Traffic Datasets	31 Datasets containing recorded traffic videos and information	31 Datasets	https://www.sciencedirect.com/science/article/pii/S1566253522000859	Visual and Numerical	Yes	Yes	Public
[34]	CIFAR-10 FEMINIST	Colour Images and industrial information	60 K colour images 805,263 samples	https://www.cs.toronto.edu/~kriz/cifar.html https://carolinesinders.com/feminist-data-set/ https://www.sciencedirect.com/science/article/pii/S0925231221007190	Visual and Numerical	Yes	Yes	Public
[53]	Crime-theft Ride-hailing Fire	Urban theft crime information Urban ride-hailing demand Urban fire records	5602 time slots 3628 1791 time slots	https://www.sciencedirect.com/science/article/pii/S0925231221007190	Visual and Numerical	Yes	Yes	Public
[49]	BIMCV COVID-19+	COVID-19 RX and CT images	1Ks patients	https://arxiv.org/abs/2006.01174	Visual and Numerical	Yes	N/A	Public
[45]	CropScape Lansat 8	Labelled rerrain data	N/A	https://www.sciencedirect.com/science/article/pii/S0168169912000798	Visual and Numerical	Yes	Yes	Public
[56]	BIT-vehicle	Several high-resolution images	N/A	https://link.springer.com/article/10.1007/s00500-021-05696-3	Visual	N/A	N/A	Public
[42]	MotionSense	Participants walking, running and navigating stairs	24 participants, 4 activities, 15 trials	https://arxiv.org/abs/1802.07802	Visual and Numerical	Yes	N/A	Public
[46]	Set5 Set14 BSD100 Urban100 N/A BSD300	Various images	5 14 100 100 91 200	https://www.sciencedirect.com/science/article/pii/S0165168420303753	Visual	N/A	N/A	Public
[70]	NYC open data Barcelona transportation data BCL: Beijing city lab Chicago data port N/A	Various types of city data for New York, Beijing, Chicago and London	N/A	https://opendata.cityofnewyork.us/ https://link.springer.com/article/10.1007/s13132-012-0084-9 https://link.springer.com/article/10.1007/s13132-012-0084-9 https://data.cityofchicago.org/ https://www.data.gov.uk/ https://www.epfl.ch/labs/lcav/page-86035-en.html http://db.csail.mit.edu/labdata/labdata.html https://www.sciencedirect.com/science/article/pii/S1566253516300252	Various types of city data: Visual, Numerical, Textual	Yes	Yes	Public
[32]	GSB Intel Lab Indoor WSN	Meteorological data (temperature, humidity, soil moisture, solar radiation and watermark) sensor measurements (temperature, humidity and luminosity) semi-automatically testbed labelled data	1.5 months of data measurements of 54 sensors N/A	https://www.epfl.ch/labs/lcav/page-86035-en.html http://db.csail.mit.edu/labdata/labdata.html https://www.sciencedirect.com/science/article/pii/S1566253516300252	Numerical	Yes	Yes	Public and Private
[60]	Google Maps	Pedestrian information in Hamburg	N/A	https://www.google.com/maps	Hybrid	N/A	Yes	Public

to process and interpret data efficiently, providing valuable insights and enabling informed decision-making for urban planners, policymakers, and stakeholders. By leveraging AI methodologies, smart cities strive to create resilient and optimised urban settings that address modern urbanisation's evolving needs and challenges (Table 5).

The presented table offers a comprehensive overview of multiple research articles within the field of AI, encompassing different research directions, methodologies, metrics, applications, and other relevant factors. The table highlights various significant points, such as the computational complexity involved in deep learning systems for disease prediction and intrusion detection, the importance of feature-level

fusion in multi-modal emotion data fusion, and the utilisation of short-term data in traffic speed prediction through Generative Adversarial Graph Attention networks. The articles span various applications, including disease prediction, emotion data fusion, traffic speed prediction, and bike demand prediction, with performance metrics such as accuracy, MAE, RMSE, and F-Measure. The involvement of IoT and the utilisation of diverse hardware platforms, such as servers, GPUs, and specific models like DGX-2, are also noted. Processing types vary between parallel and serial, while sensor types include indoor and outdoor sensors. Additionally, the articles address various aspects such as privacy, security concerns, data diversity, model optimisation, human

Table 4
Smart city information fusion plan and data categories.

Ref.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
[35]	x	x	x	x	x	x	x	x	✓	✓	x
[36]	✓	✓	✓	x	x	x	x	✓	✓	✓	x
[41]	✓	✓	✓	✓	x	x	x	✓	✓	✓	✓
[50]	✓	✓	✓	✓	x	x	x	✓	✓	✓	✓
[27]	x	x	x	x	x	x	x	✓	✓	✓	✓
[39]	✓	✓	✓	x	x	✓	x	✓	✓	✓	✓
[31]	✓	✓	✓	✓	x	x	x	✓	✓	✓	✓
[49]	x	x	x	x	x	x	x	✓	✓	✓	✓
[40]	✓	x	✓	x	x	x	✓	x	x	x	x
[28]	x	x	x	x	x	x	x	✓	✓	✓	✓
[55]	✓	✓	✓	✓	x	x	x	✓	✓	✓	✓
[56]	✓	✓	✓	✓	x	x	x	✓	✓	✓	✓
[57]	✓	✓	✓	✓	x	x	x	✓	✓	✓	✓
[58]	✓	✓	✓	✓	x	x	x	✓	✓	✓	✓
[59]	x	x	x	x	x	x	x	✓	✓	✓	✓

C1 = Sensor Data, C2 = Geographic Information, C3 = Time and Date, C4 = Event Data, C5 = Demographic Data, C6 = Environmental Factors, C7 = Social Media or Citizen Engagement Data, C8 = Identify the data sources, C9 = Collect and preprocess the data, C10 = Perform data fusion, C11 = Validate and verify the data.

interaction, explainability, uncertainty estimation, and the incorporation of external data. These studies contribute to advancing AI by improving accuracy, efficiency, and applicability across diverse domains.

Furthermore, the identified limitations of the proposed methods encompass computational complexity, limited evaluation of small datasets, lack of interpretability, sensitivity to noise and missing data, and insufficient consideration of data security and privacy. Conversely, the advantages of the proposed methods include achieving state-of-the-art performance on benchmark datasets, effective fusion of multiple data sources and modalities to enhance AI tasks, broad applicability across diverse domains, potential implementation on edge devices, interpretability in some instances, robustness to noise and missing data, and consideration of data security and privacy in specific instances.

The table provides a comprehensive and up-to-date overview of advancements in information fusion within AI. The proposed methods exhibit promising outcomes across diverse benchmark datasets and demonstrate potential for widespread application. However, it is crucial to address the identified limitations, including computational complexity, scalability, interpretability, robustness, and data security and privacy considerations.

7.5. Components of the information fusion process

Information fusion is a critical requirement for smart cities, as it enables the transformation of data originating from diverse sources into valuable insights that drive informed decision-making and support effective urban administration. By integrating and harmonising data from various sources, smart cities can unlock the full potential of their data assets. This information fusion process involves consolidating, analysing, and synthesising data to generate meaningful and actionable knowledge. By comprehending and effectively utilising these components of information fusion, smart cities can derive the maximum value from their data resources, leading to improved urban governance, optimised resource allocation, and enhanced quality of life for residents.

Table 6 provides an overview of the specific issues identified with the models in some selected papers. The particular data preprocessing steps will vary depending on the specific task at hand and the characteristics of the data. However, the techniques described above are some of the most common data preprocessing techniques used in machine learning and data mining. The preprocessing steps for deep learning models typically include data cleaning, data normalisation, and feature extraction, and traditional machine learning models include data cleaning, data normalisation, and feature selection. Natural language processing (NLP) models typically comprise data cleaning, normalisation, feature extraction, and tokenisation. Computer vision (CV)

models typically include data cleaning, data normalisation, image resizing, and image augmentation.

Different fusion methods are used in the state of the art, depending on the application and the nature of the data. Some of the research uses fuzzy logic to combine information from multiple sources. It is often used in applications with uncertain or incomplete data [35,37]. Rule-based systems fusion methods are often used in applications where the data is structured, and the relationships between the data are known [37,43,52,58,65]. An end-to-end model based on a weighted average fusion uses a neural network to learn the weights for combining information from multiple sources. It is often used in applications where the data is unstructured or the relationships between the data are unknown [23,27,29,48,50,57,80]. Model-based fusion methods assume that a statistical distribution can model the data from multiple sources. This distribution can combine the information from the different sources in a way that considers the uncertainty in the data. A Kalman filter can be used where the data is noisy or the relationships between the data change over time [44,69]. Bayesian Information Fusion considers the data’s uncertainty and prior beliefs about the data [31,40]. Hierarchical data fusion is often used in applications where the data is structured, or the relationships between the data are known [67]. The choice of fusion method depends on a number of factors, including the nature of the data, the application, and the desired performance.

Fusion methods combine data from multiple sources to create a more comprehensive and accurate world representation. The data can come from sensors such as cameras, radar, and sonar or from different sources such as other people or databases. The fusion output can be used to make better decisions, improve data quality, and identify potential problems or threats. The choice of fusion method depends on the specific application and the user’s requirements. For example, in intelligent transportation systems [25,29,50,52,68], data fusion improves traffic flow, reduces congestion, and prevents accidents. Data from cameras, radar, and sensors can be fused to create a real-time map of traffic conditions. This information can then be used to optimise traffic signals and route vehicles around congestion. Data fusion tracks objects and people in a surveillance environment in surveillance applications [35,41,45]. Data from cameras and radar can be fused to create a more comprehensive view of the environment. This information can then be used to identify potential threats and track the movement of people. In medical diagnosis, data fusion is used to improve the accuracy of medical diagnoses [31,34,48,66]. Data from medical images, such as X-rays and MRI scans, can be fused with patient records to create a more complete picture of the patient’s condition. This information can be used to make more accurate diagnoses and treatment plans. In weather forecasting, data fusion is used to improve the accuracy of weather forecasts [27,43,54]. Weather stations, satellites, and radar data can be fused to create a more

Table 5
AI techniques for smart city data integration.

Ref.	AI direction	Method	Metric	Application	IoT (Yes/No)	Hardware platform	Processing type (Serial or Parallel)	Sensor type (Indoor or Outdoor)
[48]	Increasing hidden layers reduces computational complexity, but factors should be identified and quantified more accurately.	Real-time Deep Extreme Learning System	Accuracy	Disease Prediction and Intrusion Detection	Yes	Server	Parallel	Indoor
[66]	Feature-level fusion is more common for multi-model emotion data fusion, using AI algorithms, PCA, deep learning, and simple classifiers to extract, select, train, and classify discrete basic emotions.	Data-driven multi-modal emotion information fusion: feature-level fusion and decision-level fusion	Accuracy	Data-driven multi-modal emotion information fusion	No	Medical Sensors	Parallel and Serial	Indoor
[50]	Incorporate data that affect traffic speed over short periods, less than 1 h, into deep learning models to calibrate prediction accuracy.	Generative adversarial Graph Attention network	MAE, MAPE, RMSE, Run time	Traffic speed prediction	Yes	DGX-2 with Nvidia Tesla V100 GPUs	Parallel	Outdoor
[44]	Porting the method on other cloud platforms	Cloud-Assisted Body Area Networks (CABAN) infrastructures	Recognition Accuracy Sensitivity Specificity Precision	Human activity detection and monitoring	Yes	Bluetooth Accelerometers and an Android-based personal mobile device		Outdoor
[27]	Optimising the lightweight models by integrating computational compress technologies and edge devices.	Ghost Attention Pyramid Network	Accuracy (MAE RMSE) Efficiency	Crowd counting for smart cities	No	RTX NVIDIA GPUs: RTX 3090Ti, RTX 3090, RTX 2080 super, and GTX 1080Ti	Parallel	Outdoor
[39]	LSTM gates to reset and forget emotional states based on current and historical information. Employ other modalities and heterogeneous sensor sources	CNN and Long Short-term Memory Recurrent Neural Network	Accuracy and F-Measure	Big emotion data fusion	No	Smart-phones and wearables GPU	Parallel	Outdoor
[51]	Extract more information from homogeneous data sources, such as social data, and investigate the relationship between social data and demand.	Collaborative computing and information fusion using 5G IoT: XGBoost regression model	Scores and RMSLE and ER	Bike demand prediction for bike sharing services using information fusion, collaborative learning and 5G IOT	Yes	Yes	N/A	Outdoor
[31]	Explore collaborative and lightweight ML techniques for distributed devices in IoT and resolve security and energy efficiency issues once they are discovered in the future.	Distributed ML-assisted framework and information fusion scheme	N/A	Intelligent network management and information fusion for IoT in smart cities	Yes	Sever	N/A	Outdoor
[53]	Model better semantic graphs and consider adaptive multi-scale prediction techniques.	Geographic-Semantic Ensemble Neural Network	RMSE MAPE SSIM	Urban hotspots spatiotemporal prediction	No	No	N/A	Outdoor
[49]	Investigate integrating digital twins with other explainable artificial intelligence-based techniques.	Digital twins with a Cascade recurrent convolution neural network	Mean precision rate	Medical Image Analysis: COVID-19 diagnosis	No	NVIDIA-SMI GPU	N/A	Indoor
[54]	Investigate a more optimal fusion algorithm for learning spatial-temporal features	3D spatial-temporal residual networks	Run time RMSE and MAPE	Region-based predictions in smart cities for management and security	No	P100 GPU	Serial	Indoor and Outdoor
[69]	Accuracy assessment methods Collaborative localisation Better optimisation methods INS-free filtering models Comprehensive comparisons of learning and analytics fusion techniques Better position sensors	Analytics-based and learning-based fusion	Accuracy	Multi-sensor data fusion in autonomous vehicles	Yes	Position Sensors	Parallel and Serial	Outdoor

(continued on next page)

Table 5 (continued)

Ref.	AI direction	Method	Metric	Application	IoT (Yes/No)	Hardware platform	Processing type (Serial or Parallel)	Sensor type (Indoor or Outdoor)
[46]	Data diversity in indoor localisation Integrity monitoring privacy Technique for sharing parameters across stages	Multi-scale information cross-fusion network		Super-resolution network multi-scale information fusion	No	NVIDIA Titan X Pascal GPU	Parallel	Outdoor
[70]	Data-driven approaches that can handle considerable dynamic data uncertainties and missing data. Semantic interoperability for smart cities. Consideration of temporal information. Security and Privacy.	Data-driven smart cities	Accuracy	Intelligent decision-making in smart cities	Yes	N/A	Parallel and Serial	Outdoor
[32]	Utilising aggregates or models as neighbourhood information instead of raw data. Tackle the limitations of neighbourhood timely information sharing.	Decentralised anomaly detection and unsupervised learning	Precision Recall F-measure	Anomaly detection in WSN	No	N/A	N/A	Indoor
[60]	Add human interaction as an input to the model	Reinforcement learning for human mobility routes: Reward and Best Action model	N/A	Data-driven smart cities data generation for Traffic Management	No	N/A	N/A	Outdoor
[24]	Adaptive background noise filtering. Classification focusing on target data in single-class anomaly detection algorithms.	Acoustic Classification with Deep Feature Transfer Learning: DCNN and deep belief net classification	Accuracy: Euclidean distance	Urban acoustic classification	No	N/A	N/A	Outdoor
[22]	Integrate interpretable domain data with real-world indexes to improve model comprehension and forecast potential disasters.	Deep sequence learning with spatio-temporal dynamics: Adversarial fire situation forecasting network	Run time RMSE MAPE JS	Urban Fire Situation Forecasting	No	GTX1080 GPU	N/A	Outdoor
[25]	Estimate uncertainty of the prediction system for performance reliability assessment, map partition techniques to better reflect spatial dependencies in traffic and incorporate external and anomaly traffic data	Spatial-temporal neural ordinary differential equations	Prediction Accuracy Computational Efficiency	Traffic flow prediction in data-driven cities	No	2 NVIDIA GeForce GTX 2080ti GPUs	Parallel	Outdoor
[26]	Optimise the operators in the search space of the proposed framework and incorporate more exogenous data.	Automated Spatio-Temporal Information Fusion Neural Network	RMSE MAE MAPE	Urban hotspot forecasting	No	GTX 1080 GPU	N/A	Outdoor
[30]	Acquire more data for training	Accident Information Graph Fusion Attention Convolutional Network	RMS MAE MAPE	Traffic flow (speed) prediction	No	A Windows workstation with 2 Intel Xeon Silver 4210 CPUs, 128 GB RAM, and an NVIDIA RTX 2080ti GPU with 11 GB video memory.	Parallel	Outdoor

comprehensive view of the atmosphere. This information can then be used to predict the weather more accurately.

Data fusion is used in military applications [29], such as target tracking, battlefield awareness, and weapons guidance. Radar, sonar, and electro-optical sensor data can be fused to track targets and identify potential threats. This information can then be used to guide weapons and protect soldiers. Autonomous driving is a rapidly evolving field that is being enabled by advances in data fusion technology [39,69]. Data fusion combines multiple sources to create a more comprehensive and accurate world representation. In autonomous driving, data fusion

combines data from sensors such as cameras, radar, and lidar to create a 360-degree view of the environment around the vehicle. The autonomous vehicle's control system then uses this information to decide how to navigate safely and efficiently.

The primary future use of data fusion technology is to improve the accuracy and efficiency of decision-making in various applications. Challenges that need to be addressed to improve the performance of data fusion systems include the quality of the data used in a data fusion system, which is critical to the accuracy of the results. If the data is noisy or incomplete, the fusion process results will also be noisy or incomplete.

Table 6
Information fusion components.

Ref.	Data preprocessing	Fusion methods	Fusion outputs	Uncertainty and confidence	Applications	Performance metrics
[35]	Extract, clean, and transform raw inspection reports for data fusion.	Fuzzy reasoning-based data fusion method	Integrated and fused data extracted from inspection reports.	N/A	Surveillance	Accuracy, Precision, Recall, F1-score
[65]	Clean, normalise, and select data features and extract new features to address imbalanced data.	Rule-based systems: update accept/reject flags in trained classifiers.	Binary classification.	N/A	Intrusion Detection and Security	accuracy, precision, Recall, and F1 score
[48]	Clean and normalise data to address missing values using a preprocessing layer.	End-to-end model based on a weighted average fusion.	Predicted patient health status while preserving privacy.	Probability distributions for sources and fusion	Healthcare	Accuracy, Precision, Recall, F1-score
[66]	Preprocess facial expressions, speech, and physiological signals: grayscale, resize, normalise; denoise, extract FO, compute MFCCs; denoise, filter, compute HR, RR, EDA.	Model-based fusion.	Classification based on multiple sources.	N/A	Healthcare, Security, and Marketing.	Accuracy, Precision, Recall, F1-score, Confusion matrix.
[33]	Data cleaning, Data normalisation, Data discretisation, Feature selection, Data transformation.	The weighted averaging fusion method	Predict the traffic conditions in a city or identify a cyber-attack.	Combining probability distributions with weighted data sources.	Traffic management, Disaster response	Accuracy, Precision, Recall, F1-score
[37]	Data cleaning, integration, transformation, extraction, reduction, discretisation.	Rule-based systems using fuzzy c-means.	co-clusters-based refined and integrated dataset	Probability distributions for data sources and fusion	Exploring smart data in smart cities.	F-measure, Purity, Rand Index
[29]	Data collection, data cleaning, feature extraction, and data normalisation.	Deep reinforcement learning-based fusion	Best route path that can minimise energy consumption.	Probability distributions	Environmental monitoring, industrial automation, and military surveillance. Detect anomalies in surveillance.	Energy consumption, packet loss, latency, and throughput. Accuracy, Precision, Recall, F1-score
[41]	Video cropping, Image normalisation, Feature extraction, Feature fusion.	The weighted sum of the features from the two streams	An anomaly score: a numeral that reveals the likelihood of a video including an anomaly.	N/A	early warning systems	Accuracy, Reliability, Efficiency
[43]	Data collection, Data cleaning, Data integration,	A rule-based approach for decision-level fusion	Emergency response-based decision making.	Probabilistic and Deterministic methods	Urban planning, research	Precision, Recall, F1-score, AUC
[23]	Data profiling, Data cleansing, Data transformation, Data reduction, and Data enrichment.	Quantitative and Qualitative correlation-based Emerging method.	A refined and integrated dataset with combined information	Combining weighted probability distributions from reliable sources	Traffic management, Transportation planning	MAE, MAPE, RMSE
[50]	Clean and aggregate data, construct and normalise spatial grid and graph, encode and normalise features.	The attention-based graph convolution operation	The vector of features represents the road network and the traffic speed data.	Gaussian distribution to represent the uncertainty and MSE as a measure of confidence.	Healthcare, Sports	Precision, Recall, F1-score
[44]	Data cleaning, feature extraction, Dimension reduction, and normalisation.	Kalman filter	probabilistic output	probability distributions for each data source and fused result	Traffic management	MAE, RMSE, MRE, Accuracy,
[27]	Image resizing, Background subtraction, Gaussian smoothing, Contrast enhancement, normalisation.	Ghost attention fusion	number of people in the image	Standard deviation and mean	Predicting energy consumption	Accuracy, Precision, Recall, F1-score
[67]	Data cleaning, Data formatting, Data normalisation	Hierarchical data fusion	Fused data representation for visualisation and analysis	Probability distributions	Self-driving cars	Accuracy, Precision, Recall, F1-score
[39]	Remove noise and outliers, Normalise the data	Deep learning-based fusion	the probability distribution over the different emotions.	Probability distributions	mobile bike-sharing services	Accuracy, Precision, Recall, F1-score
[51]	Noise filtering, Outlier detection, Data normalisation, Feature extraction	collaborative computing algorithm-based fusion	real-time map of the availability of bikes	N/A	Healthcare, Smart energy management	Accuracy, Precision, Recall, F1-score, Overhead, Latency
[31]	Data cleaning, data normalisation, feature selection, and Coding categorical data.	Bayesian Information Fusion	joint probability distribution	Posterior entropy and likelihood given the posterior	Traffic management, Public transportation	Accuracy, Precision, Recall, F1-score, MAE, RMSE
[52]	Data cleaning, data normalisation, feature selection, and Coding categorical data.	decision-based fusion based on a weighted majority voting rule	probability distribution of congestion levels	Bayesian approach	Traffic predictions	Accuracy, Precision, Recall, F1-score,
[68]	Data cleaning, Data normalisation, Data aggregation, and Feature extraction.	Hybrid (Data fusion, Decision fusion, Knowledge fusion)	Fused data representation for visualisation and analysis	Entropy, Bayesian networks	Healthcare, Finance	Accuracy, Precision, Recall, F1-score,
[34]	Data collection, Data cleaning, Data partitioning, and Data encryption.	blockchain federated learning-based fusion	Updated models or knowledge bases based on the fused data	Bayesian federated learning and entropy		Accuracy, Precision, Recall, F1-score,

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Table 6 (continued)

Ref.	Data preprocessing	Fusion methods	Fusion outputs	Uncertainty and confidence	Applications	Performance metrics
[53]	Data cleaning, Data normalisation, Feature extraction	Combining PredRNN and GC-PredRNN	prediction of the spatiotemporal dynamics of urban hotspots	Bayesian approach	Traffic congestion, crime	RMSE, MAE, F1 score, AUC
[45]	Image resizing, Image normalisation, Image augmentation,	Hybrid fusion: CNN-based and decision-based (voting)	segmentation masque	Bayesian approach	Object tracking	Accuracy, Precision, Recall, F1-score,
[40]	Data cleaning, Data normalisation, Data transformation, Feature selection,	Bayesian fusion, Dempster-Shafer fusion, and Neural network fusion, the fusion method used, are based on the task.	fused representation of the environment	Probability distributions and Markov chain Monte Carlo (MCMC)	Traffic management, crime prevention	Accuracy, Precision, Recall, F1-score, Fusion time, Energy
[80]	Data normalisation, Feature selection, Data sampling	Two fusion methods are used: Federated meta-learning-based fusion and Reinforcement learning-based fusion.	Decision made	Bayesian approach	Healthcare systems, Smart factories	Resource utilisation, Task completion time, Makespan, Cost, Robustness
[54]	Data normalisation, Feature selection, Data sampling	LMST3D-ResNet-based fusion (deep learning-based fusion)	set of predictions	Bayesian approach	Power demand forecasting	RMSE, MAE, R-squared
[55]	Noise removal, Outlier removal, Data alignment, Feature extraction	Responder-dependant Additive Information Fusion (RAIF). It is a machine learning-based method.	Vehicle position and orientation	weighting approach	Healthcare and traffic management	MSE, RMSE, MAE, Accuracy, Precision, Recall
[69]	Data cleaning, Data integration, Data transformation, Data reduction, Feature selection	Kalman filter-based fusion and learning-based fusion	Estimated state: position, velocity, acceleration	Bayesian approach	Autonomous driving	Accuracy, Precision, Recall, Robustness, Complexity
[57]	Data collection, Data cleaning, Data normalisation, Data augmentation, Feature extraction, labelling	space-weighted information fusion (SWIF) approach	the fused vector that contains the information from the CAV and the neighbouring vehicles	N/A	Traffic management	Collision, lane change success, time-time, fuel, comfort
[58]	Data cleaning, Data normalisation, Feature selection	weighted sum rule	The categorical variable represents the predicted vehicle.	confusion matrix	Traffic management	Accuracy, Precision, Recall, F1-score, MAP, ROC, AUC
[46]	Normalisation, cropping	Multi-scale cross (MSC) fusion	high-resolution image.	Bayesian	image compression and transmission.	PSNR, SSIM, VIF
[24]	Data acquisition, Data cleaning, Data sampling, Feature extraction, Feature normalisation	Features from multiple CNNs are concatenated.	Predicted class of the urban acoustic signal.	Bayesian approach	Environmental monitoring, Disaster response	Accuracy, Precision, Recall, F1-score, MAP, ROC, AUC
[25]	Data cleaning, Feature extraction, Data normalisation,	two-steps of the fusion process: data fusion and model fusion	predicted traffic flow at a specific time and location.	Bayesian approach	Transportation planning	MAE, RMSE, MAPE, NMAE, NRMSE

Many different data fusion algorithms are available, each with advantages and disadvantages. The choice of algorithm depends on the specific application and the system's requirements. Data fusion can be computationally expensive, especially when large amounts of data are involved. This can be a challenge for real-time applications. When data from multiple sources is combined, it is essential to consider this process's privacy and security implications. For example, if data from medical records is fused with data from social media, this could reveal sensitive information about individuals. It is essential to protect individuals' privacy and security when using data fusion techniques.

The specific metrics used for data fusion will depend on the particular application. For example, accuracy, Recall, and F1-score may be the most critical metrics in a medical diagnosis application, while precision may be more critical in a surveillance application. A confusion matrix is a table that shows a data set's actual and predicted classifications. It can visualise the system's performance and identify improvement areas. The MAE is the average of the absolute errors between the predicted and actual values. It is a measure of the accuracy of the system. The RMSE is the square root of the average of the squared errors between the predicted and actual values. It measures the system's accuracy and is more sensitive to outliers than the MAE. The MAPE is the average of the absolute percentage errors between the predicted and actual values. It measures the system's accuracy and is expressed as a percentage. The ROC curve plots the real positive rate against the false positive rate for a range of thresholds. It can evaluate the system's performance and select

the optimal point. The AUC is the area under the ROC curve. It measures the system's overall performance and is independent of the threshold. The choice of performance metrics will depend on the specific application and the system's requirements. It is essential to select metrics relevant to the application that will allow the system's performance to be accurately evaluated.

It is essential to use multiple metrics to evaluate the performance of a data fusion system. This will help get a complete picture of the system's performance. The choice of performance metrics should be based on the specific application of the data fusion system. No single metric is perfect, and each metric has its limitations. It is essential to be aware of the metrics' rules and interpret the results accordingly. Statistical methods can be used to analyse the performance metrics results and identify trends and patterns. This can help improve the understanding of the system's performance and identify areas where it can be improved. The performance metrics should be used to iterate and improve the data fusion system. This can be done by adjusting the system's parameters or using different fusion algorithms.

8. Smart city information fusion: a cutting-edge application

8.1. Education applications

In the realm of education, Information Fusion serves as the innovative bridge between diverse sources of knowledge and the learning

process. This dynamic approach amalgamates data from various educational channels, seamlessly integrating digital resources, textbooks, and interactive media to create a comprehensive learning experience. Imagine an educational application where Information Fusion is the backbone, effortlessly blending real-time updates, scholarly articles, and interactive simulations. Students benefit from a holistic understanding of subjects as the app synthesises information from textbooks, online courses, and cutting-edge research papers.

Teachers armed with this fusion-powered tool can tailor their lessons with the latest insights, adapting to the evolving educational landscape, as shown in Fig. 12. The application becomes a hub for collaborative learning, fostering an environment where students and educators collectively contribute to a shared pool of knowledge. Through Information Fusion, traditional boundaries between disciplines blur, encouraging a multidisciplinary approach to education. The application becomes a virtual academy, nurturing subject-specific expertise, critical thinking, and problem-solving skills.

Assessment tools integrated with Information Fusion ensure that evaluation is not just about memorisation but understanding and applying concepts across diverse sources. This fosters a deeper connection to the material and prepares students for a world where information is constantly evolving. The application's user interface becomes intuitive and personalised, adapting to individual learning styles. Whether visual, auditory, or kinaesthetic, Information Fusion caters to diverse learning preferences, creating a genuinely inclusive educational experience. Furthermore, this fusion-driven application extends beyond formal education, becoming a lifelong learning companion. Users can stay informed about the latest developments in their field, fostering a culture of continuous learning and professional growth [84,85].

In conclusion, information fusion is a linchpin in advancing education and developing smart cities. Seamlessly integrating diverse data sources empowers educators and city planners to make informed decisions, optimise resources, and create environments tailored to the unique needs of individuals and communities alike.

8.2. 6G communication applications

Information Fusion is pivotal in advancing 6G communication and optimising smart city infrastructure. In the context of 6G, which aims to provide unprecedented connectivity and data speeds, Information Fusion becomes the glue that binds together diverse data sources. It involves integrating information from various sensors, devices, and networks to create a comprehensive and accurate picture of the

environment.

In the realm of 6G communication, Information Fusion enhances data transmission efficiency by combining inputs from multiple sources. This ensures reliable and low-latency communication and facilitates the seamless integration of different technologies, such as holographic communication and advanced AI applications. Fusing data from different communication modalities enables a more holistic understanding of user needs, leading to personalised and context-aware services.

Information Fusion is instrumental in creating an interconnected and intelligent urban ecosystem in the context of smart cities. By aggregating data from sensors embedded in infrastructure, public services, and IoT devices, cities can gain real-time insights into traffic management, energy consumption, and environmental conditions. This comprehensive data synthesis allows for predictive analytics, enabling cities to address congestion, pollution, and energy inefficiency proactively.

Moreover, Information Fusion is essential for enhancing the security and resilience of 6G networks and smart city systems. Consolidating data from various security sources enables more effective threat detection and response mechanisms. This is particularly crucial as the increased connectivity in 6G and smart cities amplifies potential attack surfaces [82,86].

In conclusion, Information Fusion serves as a linchpin in the evolution of 6G communication and the development of smart cities. Its ability to integrate and interpret vast amounts of data is foundational to the seamless operation of advanced communication networks and the optimisation of urban living. As technology advances, the role of Information Fusion will likely become even more pronounced in shaping the future landscape of connectivity and smart urbanisation (Fig. 13).

8.3. Robotics applications

Information Fusion emerges as a crucial enabler in robotics and smart cities, fostering synergy between these two transformative domains. Information Fusion acts as the cognitive backbone, seamlessly integrating data from diverse sources to enhance the capabilities of robotic systems within smart urban environments.

In the context of robotics, Information Fusion plays a pivotal role in sensor integration, amalgamating data from various sensors such as cameras, LiDAR, and GPS to provide robots with a comprehensive perception of their surroundings. This enhances navigation and obstacle avoidance and contributes to the development of more context-aware and adaptable robotic systems.



Fig. 12. Synergizing education applications in the smart city landscape through information fusion [85].

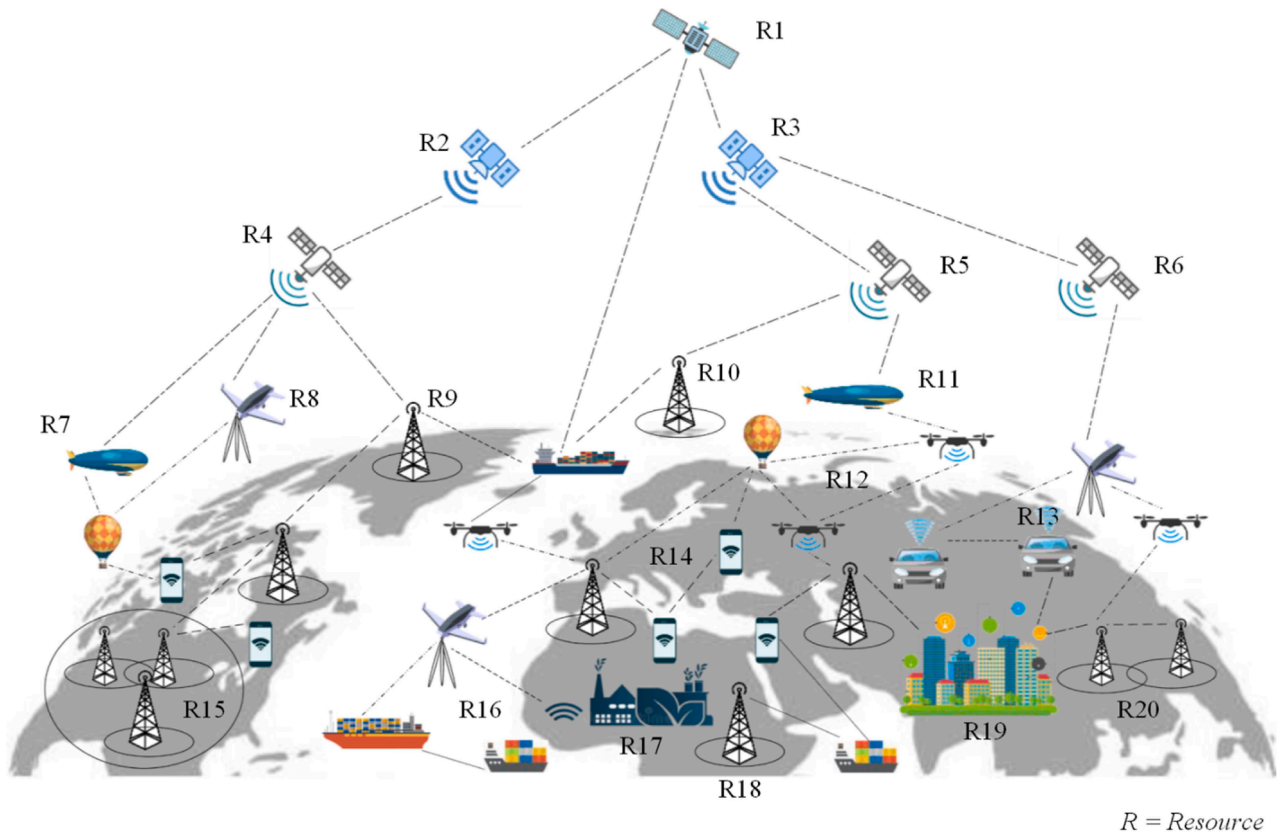


Fig. 13. Integration of 6G communication technologies for smart city and information fusion.

Smart cities, characterised by interconnected infrastructure and IoT devices, benefit significantly from Information Fusion. The technology aggregates data from sensors embedded in urban spaces, including traffic cameras, environmental monitors, and smart grids. This consolidated data serves as the foundation for optimising city operations, enabling efficient traffic management, resource utilisation, and environmental monitoring.

Furthermore, Information Fusion facilitates human-robot collaboration in smart cities, allowing robots to interpret and respond to human behaviour more effectively. This is particularly relevant in scenarios such as autonomous vehicles navigating urban landscapes or robotic assistants interacting with residents. Information fusion enables robots to make informed decisions based on a holistic understanding of the environment and human interactions.

In terms of security, Information Fusion enhances the resilience of both robotic systems and smart city infrastructure. Synthesising data from surveillance cameras, motion detectors, and other security measures enables more robust threat detection and response mechanisms, contributing to overall safety in urban environments [80].

In essence, Information Fusion acts as the linchpin connecting robotics and smart cities, facilitating a symbiotic relationship where robots contribute to the efficiency and sustainability of urban living, and smart cities provide the rich data ecosystem necessary for robots to operate intelligently. As these fields continue to evolve, the role of Information Fusion is poised to play a pivotal role in shaping the future landscape of smart, responsive, and collaborative urban environments. The robotic part is seen in Fig. 14 [87].

1. Robot Arm: This is the mechanical limb responsible for carrying out physical tasks. It could be anything from manufacturing to handling objects in a smart city environment.

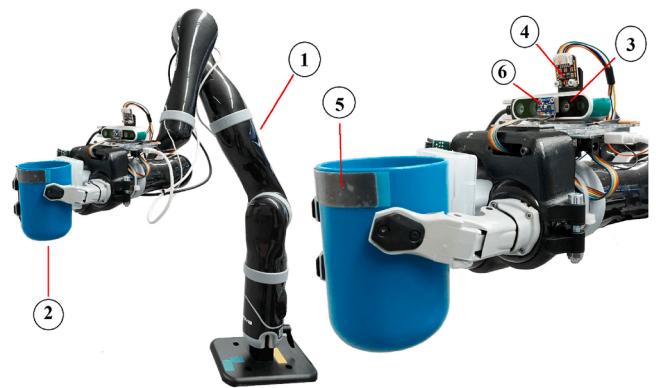


Fig. 14. The robotic part. (1) Robot arm (2) Cup (3) Camera (4) Distance sensor (5) Force and Capacitive sensor. (6) Environmental sensor [87].

- 2. Cup: This component could be part of the end-effector of the robot arm. It is interesting to think about what tasks the robot might perform that involve interacting with a cup.
- 3. Camera: Visual input is crucial for many robotic applications. The camera allows the robot to "see" its environment, which is essential for tasks that require object recognition, navigation, or interaction.
- 4. Distance Sensor: This sensor likely helps the robot perceive its proximity to objects or obstacles in the environment. This is crucial for navigation and avoiding collisions.
- 5. Force and Capacitive Sensor: These sensors provide information about the forces applied by the robot's end-effector. This is valuable for tasks that require precision, such as delicate object manipulation or tasks in which the robot needs to apply a specific amount of force.
- 6. Environmental Sensor: This sensor could measure various environmental conditions like temperature, humidity, or air quality. In a

smart city context, monitoring environmental parameters is essential for ensuring the well-being of the urban population.

Now, let us talk about information fusion. In robotics, information fusion combines data from multiple sensors to obtain a more accurate and comprehensive understanding of the environment. In this case, the robot is likely integrating data from the camera, distance sensor, force and capacitive sensor, and environmental sensor to make informed decisions.

For example, it might use visual data from the camera to identify the cup, the distance sensor to determine its proximity, and the force sensor to ensure a delicate grasp. The environmental sensor could provide context about the robot is operating conditions.

In a smart city scenario, such robotic systems could be deployed for tasks like automated delivery, waste management, or even infrastructure maintenance. The integration of these sensors allows the robot to adapt to dynamic and unpredictable urban environments, making it a valuable asset in developing smart cities.

8.4. Cybersecurity applications

In the intricate landscape of smart cities, where the fusion of cutting-edge technologies defines urban evolution, the role of cybersecurity intertwined with information fusion emerges as a linchpin of resilience. The fabric of interconnected elements, encompassing IoT devices, communication networks, and centralised control systems, unveils a vast attack surface susceptible to a spectrum of cyber threats. A comprehensive cybersecurity framework, deeply rooted in information fusion, becomes imperative in response. This fusion orchestrates real-time data integration from diverse sources, forming the backbone for agile anomaly detection and, consequently, proactive threat mitigation.

The expansive threat panorama within smart cities spans traditional malware to sophisticated assaults targeting critical infrastructure. A multifaceted cybersecurity strategy must be employed to navigate this

complexity, leveraging the insights derived from information fusion to craft adaptive defence mechanisms. Moreover, as smart cities become data-centric entities, data integrity and privacy concerns arise. In this context, information fusion necessitates implementing robust encryption, stringent access controls, and advanced data anonymisation techniques to safeguard sensitive information from unauthorised access or manipulation.

In the unfortunate event of a cyber breach, the efficacy of incident response and recovery hinges on the speed and precision of insights provided by information fusion. Rapid identification of the attack source and impact enables the orchestration of targeted response measures, minimising damage and facilitating swift recovery. Collaboration emerges as a force multiplier in the cybersecurity arsenal of smart cities, as seen in Fig. 15, with information sharing acting as a conduit for collective intelligence. This collaborative ethos extends beyond governmental agencies to encompass private enterprises and engaged citizens, fortifying the city’s overall cybersecurity posture [33,43].

Adaptability becomes paramount in the face of evolving cyber threats. Integrating machine learning and artificial intelligence into information fusion systems enables continuous learning from patterns and anomalies. This adaptive security approach empowers smart cities to stay ahead of emerging threats, learning and evolving in real-time.

Compliance with cybersecurity regulations and standards adds another layer of complexity. Information fusion, however, serves as a tool for automating compliance checks, ensuring that the smart city adheres to established security protocols. In essence, the intricate dance between cybersecurity and information fusion within smart cities safeguards against potential threats and fosters an environment where technological innovation can flourish securely. This collaborative and adaptive approach marks the trajectory toward a resilient and secure future for urban landscapes in the digital age [88].

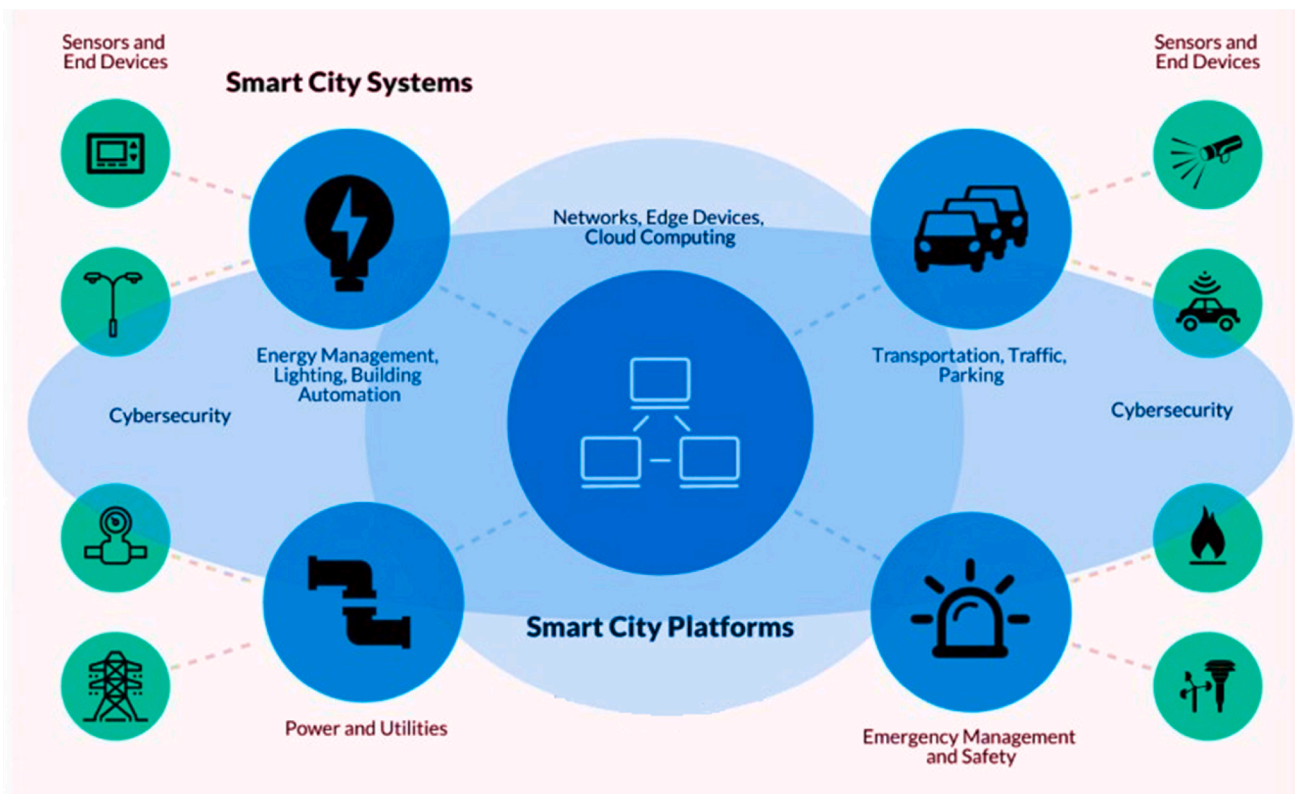


Fig. 15. A fusion of cybersecurity applications in smart environments.

8.5. MedTech applications

MedTech, an abbreviation for medical technology, is a swiftly evolving domain that leverages technological advancements to enhance the provision of healthcare services. From wearable gadgets and remote patient monitoring to advanced imaging technologies and robot-assisted surgical procedures, MedTech is fundamentally transforming our approach to healthcare. A noteworthy trend in MedTech is the growing emphasis on preventive healthcare. Notably, wearable devices continually monitor vital signs, delivering real-time health data to individuals and healthcare practitioners. This focus on prevention and early intervention can potentially enhance patient outcomes substantially.

Regarding Information Fusion, MedTech relies on amalgamating data from diverse origins. This includes patient records, data generated by wearable devices, medical imaging, and other sources amalgamated to construct a thorough and accurate representation of an individual's health. Information Fusion empowers healthcare professionals to make more informed decisions, resulting in superior diagnostics, personalised treatment plans, and an overall enhancement in patient care.

In contrast, smart cities embody a visionary approach to urban living, employing digital technologies to optimise municipal operations and elevate residents' quality of life. This involves integrating Internet of Things (IoT) devices, sensors, and data analytics to ameliorate different facets of urban existence, such as transportation, energy management, and public safety, as seen in Fig. 16. Information Fusion plays a crucial role in smart cities by assimilating data from a myriad of sources, including traffic sensors, surveillance cameras, and environmental monitoring devices. This consolidated data equips city authorities with a comprehensive understanding of the urban environment, enabling data-driven decisions for more effective city management [72].

The convergence of MedTech and smart cities is evident in the potential to establish an all-encompassing and interconnected healthcare ecosystem within urban settings. Smart cities can integrate MedTech solutions to amplify public health initiatives and emergency response systems. For example, wearable devices can be deployed to monitor

citizens' health in real-time, seamlessly integrating this data into the broader smart city infrastructure. Consequently, smart cities can proactively tackle public health issues, optimise resource allocation in healthcare facilities, and enhance the community's overall well-being.

Fundamentally, Information Fusion is the linchpin that interconnects MedTech and smart cities. It facilitates the seamless integration of data from diverse sources, fostering a comprehensive and collaborative approach to healthcare within the urban landscape. As these technologies advance, the symbiosis between MedTech and smart cities holds the potential to create urban environments that are more resilient, efficient, and health-conscious [89].

8.6. Intelligent transportation systems application

The implementation of information fusion greatly enhances the resolution of difficulties in Intelligent Transportation Systems (ITS) inside smart cities, as displayed in Fig. 17. The complex and convoluted structure of urban mobility, which includes many modes such as highways, trains, and public transit, requires a comprehensive strategy. Information fusion efficiently combines data from several sources, such as traffic sensors, GPS systems, and security cameras, to provide a complete and thorough picture of the transportation environment. This comprehensive technique enables immediate management of traffic, enabling flexible control of signal systems and adaptable routing to reduce congestion. The integration of data successfully addresses safety and security problems, hence improving situational awareness and enabling rapid reactions to situations. Furthermore, the integration of information from many sources, such as car emissions, traffic patterns, and alternative transportation choices, plays a significant role in promoting environmental sustainability. This allows communities to effectively adopt and enforce eco-friendly laws. Public transport systems may be enhanced by optimizing the integration of ticketing systems, GPS tracking, and passenger load data. This optimization helps to ensure that the services provided are dependable and efficient. Furthermore, information fusion enhances user capabilities by providing customized,

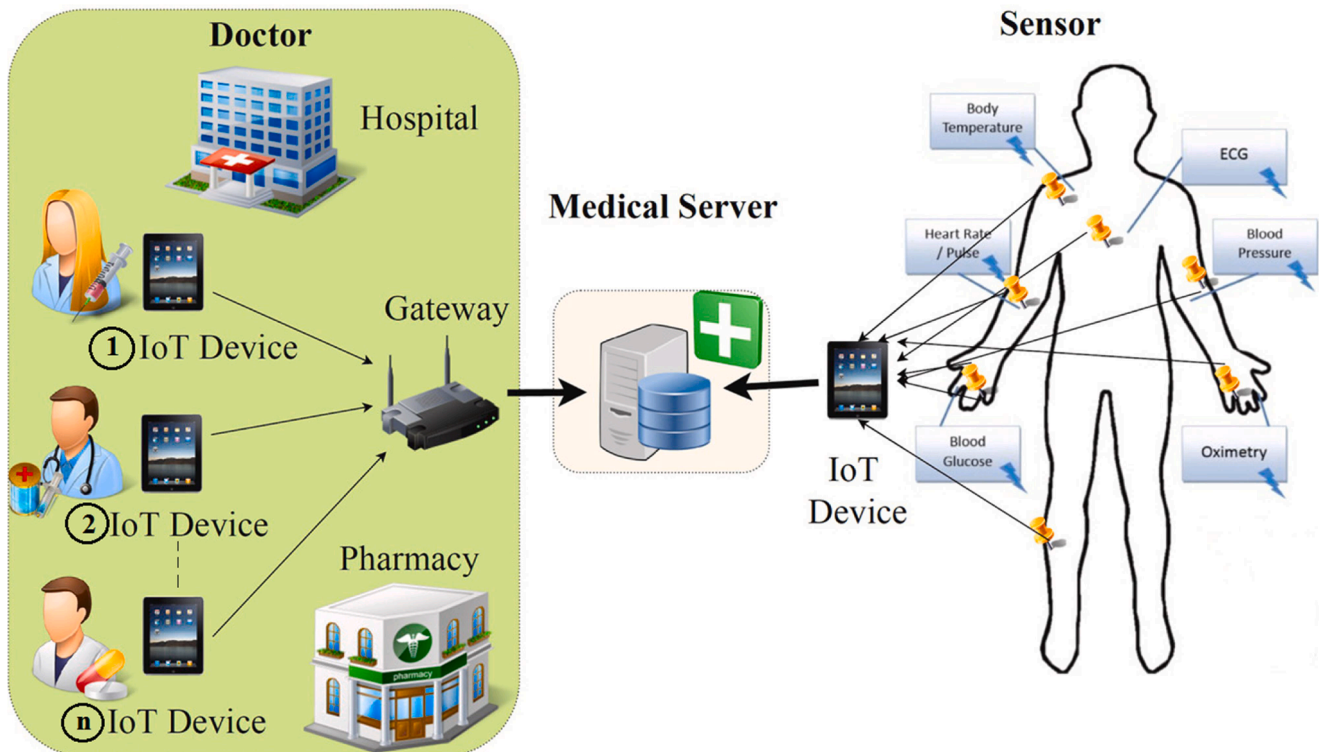


Fig. 16. Convergence of MedTech innovations in smart city information fusion.

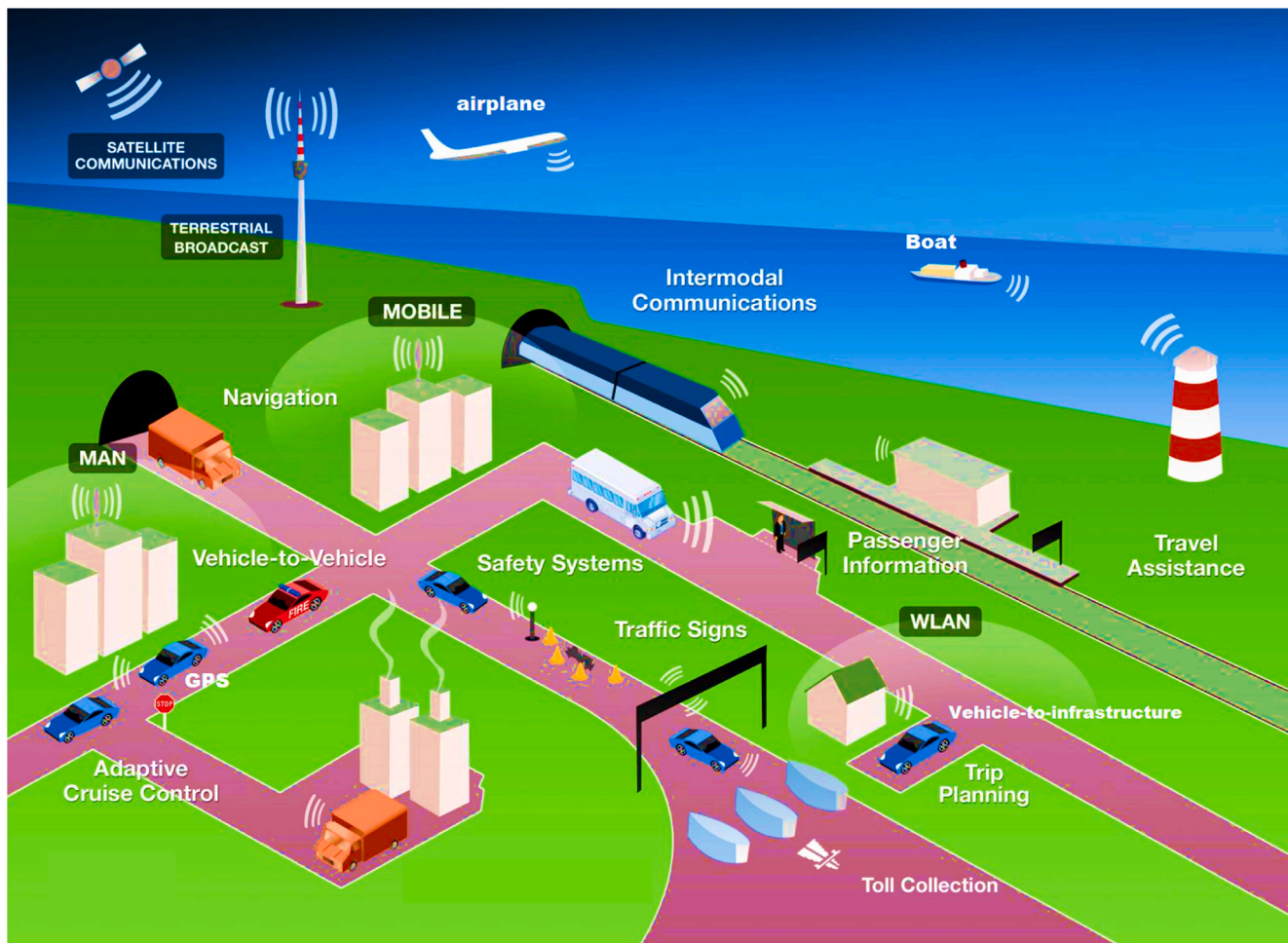


Fig. 17. Integration of Intelligent Transport Systems within the context of smart cities' information fusion [91].

up-to-date information like weather forecasts, traffic conditions, and public transport timetables, therefore promoting well-informed decision-making. Information fusion is crucial in smart cities as it enables the creation of a highly networked and data-driven Intelligent Transportation System. This system effectively tackles obstacles and enhances the urban mobility experience for inhabitants [90].

8.7. Managing emergencies and crises within smart cities

Information fusion management of emergencies and crises in a smart city involves using technology and data integration to enhance readiness, response, and recovery processes. Information fusion may be used to efficiently address the many types of crises listed below [92,93]:

1. Natural Emergencies:

- Extreme Weather Events: Deploy weather sensors and forecasting systems that provide up-to-the-minute information on hazardous weather conditions. Information fusion can combine weather data with building sensors to automatically activate alarms and direct people to designated shelters.

2. Technological Emergencies:

- Fire: Implement intelligent fire detection systems equipped with sensors to identify smoke and flames. Information fusion may amalgamate these technologies with building automation to initiate automated evacuation processes and alert emergency services.
- Hazardous Materials Accidents: Deploy sensors to monitor hazardous materials and combine the collected data with geographical

information systems (GIS) to effectively track and identify locations at risk of spills. Information fusion may activate automated alarms and reaction strategies.

- Chemical/Biological/Radiological (CBR) Emergencies: Employ sensors to surveil CBR substances inside educational facilities. Integrating this data with up-to-the-minute meteorological information may aid in forecasting the spread of dangerous compounds in emergency situations.

3. Human-Caused Emergencies:

- National Emergency (War, Terrorism): Deploy surveillance technology and crowd monitoring systems to identify and track abnormal behaviours. Information fusion is the process of combining data from security cameras, social media, and other sources in order to provide a complete and thorough understanding of a situation for emergency response purposes.
- Civil Disorder: Utilize social media analytics and crowd monitoring techniques to detect and pinpoint possible areas of civil unrest. Data integration via information fusion enables the efficient allocation of resources and the synchronisation of responses by law enforcement agencies.

4. Cross-Cutting Solutions:

- Data Integration and Analytics: Implement a centralized Emergency Operations Centre (EOC) that consolidates data from several sources. Advanced analytics may enhance predictive modelling, optimise resource allocation, and facilitate decision-making in emergency situations.
- Communication Systems: Deploy an integrated communication platform that consolidates diverse communication channels, such

as social media, emergency alerts, and public announcements, to guarantee prompt and efficient distribution of information to citizens, emergency responders, and pertinent authorities.

- Drone Technology: Employ unmanned aerial vehicles equipped with sensors to swiftly evaluate emergency scenarios. Drone data may be integrated with GIS and other pertinent data sources to provide immediate and comprehensive situational awareness.

Implementing an information fusion strategy in a smart city allows authorities to improve their capacity to swiftly identify, evaluate, and address crises, hence enhancing overall resilience and reducing the effect on the community.

9. Conclusion

The development and optimisation of smart cities rely on the fusion of information, a task that can be accomplished with machine learning and deep learning techniques. Machine learning algorithms such as classification, regression, and clustering can draw meaningful insights and patterns from diverse data sources, including social media, sensors, and Internet of Things devices. By leveraging these algorithms, smart cities can enhance resource allocation, public safety, and overall quality of life. Anomaly detection, data correlation, and future trend forecasting are among the capabilities of these algorithms. On the other hand, deep learning enables smart cities to process complex and unstructured data efficiently, leading to more accurate forecasts and deeper insights into urban dynamics. Despite challenges such as data privacy, security, robust algorithms, and computational infrastructure, smart cities hold great promise for creating sustainable, efficient, and livable urban environments for their residents.

In addition, the field of information fusion for smart cities requires more datasets to facilitate the development and evaluation of fusion models. Diversified and extensive datasets can enhance the accuracy and robustness of information fusion systems. Adhering to trustworthy artificial intelligence principles in information fusion for smart cities is crucial. Promoting transparency, accountability, and fairness in developing and implementing fusion models is essential to gaining public confidence and acceptance of smart city technologies.

It is essential to incorporate explainable AI methodologies into information fusion models designed for smart cities to ensure that the decision-making process is understood and trusted. Transparent and interpretable models allow stakeholders to verify and understand the fusion outcomes. Ongoing research and advancement are crucial to overcome challenges and limitations in the field of information fusion for smart cities. Data quality assurance, scalability, real-time processing, and privacy-preserving techniques should be explored to drive further progress.

The successful fusion of information in smart city applications requires effectively integrating contextual knowledge and domain expertise. Combining machine learning techniques with subject matter expertise results in more precise fusion outcomes sensitive to the specific urban context. Privacy protection and data security should be considered ethical considerations in smart city information fusion research. Implementing robust privacy-preserving techniques and secure data handling practices is necessary to mitigate risks and uphold responsible data fusion practices. The future opportunities include exploiting advanced sensor technologies such as IoT and edge computing, including machine learning for better decision-making, and developing standardized frameworks for rapid information interchange across several systems.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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