Sustainable Cities and Society 79 (2022) 103663

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Federated learning enabled digital twins for smart cities: Concepts, recent advances, and future directions

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ARTICLE INFO

Keywords:
Digital Twin
Federated Learning
Internet of Things
Virtual replica
Smart city

ABSTRACT

Recent advances in Artificial Intelligence (AI) and the Internet of Things (IoT) have facilitated continuous improvement in smart city based applications such as smart healthcare, transportation, and environmental management. Digital Twin (DT) is an AI-based virtual replica of the real-world physical entity. DTs have been successfully adopted in manufacturing and industrial sectors, they are however still at the early stage in smart city based applications. The major reason for this lag is the lack of trust and privacy issues in sharing sensitive data. Federated Learning (FL) is a technology that could be integrated along with DT to ensure privacy preservation and trustworthiness. This paper focuses on the integration of these two promising technologies for adoption in real-time and life-critical scenarios, as well as for ease of governance in smart city based applications. We present an extensive survey on the various smart city based applications of FL models in DTs. Based on the study, some prominent challenges and future directions are presented for better FL–DT integration in future applications.

1. Introduction

During recent times, the world has encountered different problems due to urbanization such as urban poverty, high costs, congestion of traffic, shortage of shelter, lack of financial support, rising crimes, degradation of the environment, and inequality (OBrien, Pike, & Tomaney, 2019). Governments are also trying to rectify these problems. According to a recent estimate of United Nations (He et al., 2021), by the end of 2050 around 68% of the entire population would be dwelling in cities. Various studies have examined the trend at which urbanization happens across the world and the need for improvement in quality of life (Li, Zhang, Mirzaei, Zhang, & Zhao, 2018; Zhang, 2020). This has led the governments to think of building smart cities with innovative ideas and technologies (Hakak, Khan, Gilkar, Imran, & Guizani, 2020; Zhang, 2016). Recent developments in technologies like cyber–physical systems, high-performance computing, cloud computing and IoT have encouraged the industries to adopt these in real-world environment. This adoption has enabled the industries to develop and design replications digitally for their products, devices, processes and systems. These digital replications are termed as Digital Twins (DTs) (Jones, Snider, Nassehi, Yon, & Hicks, 2020; Tao, Zhang, Liu, & Nee, 2018). To be more specific, DTs are developed for replicating a physical component in the real-world so that it acts as a mirror to the actual component. DTs were first adopted in manufacturing sector. As per the Gartner survey report, around 13% of industries developing IoT products are using DTs and 62% are adopting the technology and are in the process of designing. The DTs are characterized by the following properties.

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[1] The work of Quoc-Viet Pham was supported by the National Research Foundation of Korea (NRF) Grant funded by the Korea Government (MSIT) under Grant NRF-2019R1C1C1006143.

https://doi.org/10.1016/j.scs.2021.103663
Received 30 August 2021; Received in revised form 30 December 2021; Accepted 30 December 2021
Available online 19 January 2022

Table 1
Difference between DT and Existing Technologies.

Technology	Difference from DT
Simulation	Not dynamic and no real-time connectivity.
ML	Not a mirror of the physical entity. (twin is not available)
Digital Prototype	Not designed using IoT components.
Optimization	Process and products are not simulated. Tests are not conducted in real-time.
Autonomous Products	Do not have the characteristic of self-learning.
Agent Models	Do not have a real-time twin of the physical entity.
Digital Shadows	Data of physical entity is saved as a copy and allows data to flow from physical entity to the digital object which is a one-way communication.
VFDM	No real-time synchronization of data.
Product Avatar	No concept of feedback.
Holons	Basic computer-integration tool for manufacturing.
Digital Model	Data is manually exchanged and the current state of the model in real-time is not showcased.
Digital Product Memory	Can be considered as an instance of DT. A specific physical part is monitored and information exchange is initiated.
Intelligent Products	DT is an extension of this technology which does not use the recent technologies like IoT, ML, big-data and cloud architectures.

- There is always a real-time connection between the DT and the physical entity.
- The DT can self-learn according to the environment and will adapt itself as well as guide the physical entity.
- Continuous analysis of the data is performed using machine learning (ML) techniques and does not stop with one time forecast.
- Time series data is available for continuous monitoring and also transferred to the ML model.
- They provide services specific to the domain and also prioritize the services as per the current requirement of the industry.

The concept of digitizing and twinning or mirroring is not totally new. There are a few other similar technologies that preceded DTs like a digital shadow, semantic Virtual Factory Data Model (VFDM), product avatar, digital product memory, intelligent product, and holons. But DTs have novel and clear applications that are exclusive, which makes its adoption in real-time better. The difference between DT and existing technologies is depicted in Table 1. DT technology is best suited for the process of urbanization and smart city developments like smart manufacturing, maintaining and managing IoT-based industrial products and they provide better stakeholder satisfaction. A smart city is an urban area equipped with sensors and other IoT devices that collect the data continuously, which can be used to extract the patterns from the data and thus can be used to enhance the governance and administration of smart cities (Jararweh, Otoum, & Al Ridhawi, 2020; Kumar et al., 2021). The administration and governance in a smart city include managing several applications such as smart grid, smart homes, smart healthcare, and intelligent transport systems (Singh, Jeong et al., 2020) as depicted in Fig. 1. DT can create a virtual replica of a smart city and simulate factors such as climatic conditions, the trajectory of the people, traffic, and power usage. This can help in inclusive and efficient decisions. A DT of a smart city relies on high-quality, long term data for decision making, which limits the advantages of a smart city DT during any crisis such as pandemic, traffic congestion, and natural calamities (Fan, Jiang, & Mostafavi, 2020; Shirowzhan, Tan, & Sepasgozar, 2020).

Apart from this, the industrialists and the manufacturers of new IoT products are able to forecast the actual behavior and outcome of the product even before being manufactured or assembled as per the requirement. In future, DTs would be widely used in data sensitive applications like air force vehicles, surveillance, healthcare as a result of their extraordinary features (Fuller, Fan, Day, & Barlow, 2020; Liu, Fang et al., 2021; Rasheed, San, & Kvamsdal, 2020). DTs are designed to enable prediction and forecasting using AI. For the purpose of this, huge data needs to be analyzed and archived. DTs also exchange huge data from one location to another location and a high level of trust is required for handling such enormous sensitive data. This is the biggest challenge in the current scenario. FL is a technology which has the potential to mitigate data privacy issues by allowing the end-users to train the global model in their local environment or local device and update the parameters alone in the global model after the training process (Mothukuri, Khare et al., 2021; Mothukuri, Parizi et al., 2021; Niknam, Dhillon, & Reed, 2020). In a smart city, the most sensitive and critical use case is healthcare (Khatoon, Rahman, Alrubaian, & Alamri, 2019). This plays an important role in the governance of an urban area. Let us consider the application of DT in personalized medicine (Björnsson et al., 2020), a sub-domain of healthcare, as illustrated in Fig. 2 as a use case for smart city governance. Let us consider that an individual is affected by a disease. Using the DT concept, multiple copies of DT for the patient are developed using various computational models. Each DT of the patient is treated computationally using various drugs and also with different dosages. The drug that best cures one of the DTs is chosen as the drug for treating the individual patient. This data is too sensitive and requires high level of data privacy. Instead of communicating the data from the DT to the cloud or any storage area for performing the predictive analysis using ML models, FL can be utilized, whereby, the doctor can use the global model, and the data will be trained locally by maintaining sensitivity and privacy.

Although FL and DT technologies are extensively explored by recent researchers for smart city based applications, most of the studies are done separately. With respect to DTs, few well-known surveys are presented focusing on techniques that could be utilized for implementing DTs in domains like IoT, edge networks (Chukhno et al., 2020), industrial manufacturing sectors (Leng et al., 2021), and healthcare (Croatti, Gabellini, Montagna, & Ricci, 2020). With regards to FL, surveys are presented with the usage of FL in mobile edge networks (Lim et al., 2020), healthcare informatics (Xu et al., 2021), etc. With respect to DT for smart cities, some surveys discuss the tools and techniques for deploying smart cities in real-time using DTs (Mylonas et al., 2021), DT models for urban planning (Dembski, Wössner, Letzgus, Ruddat, & Yamu, 2020), smart campus DTs using social IoT (Zaballos, Briones, Massa, Centelles, & Caballero, 2020), 3D city models using DTs for mapping local vulnerabilities (Shahat, Hyun, & Yeom, 2021) and smart city DT for enabling citizens to report on failures and problems (White, Zink, Codecá, & Clarke, 2021). Whereas, with respect to FL-enabled smart cities, there are few works on smart city sensing services (Jiang, Kantarci, Oktug, & Soyata, 2020), applications of FL in smart cities (Zheng et al., 2021) and trust management in smart cities using FL (Liu, Guo et al., 2021). Different from existing surveys, in this work, we provide a study on the use of FL for DTs and their applications in smart city based scenarios. To the best of our knowledge, this survey is the very first attempt at the integration of FL and DT for smart city-based applications as illustrated in Table 2. The major advantage of integrating FL and DT is that they have their own merits and are being utilized in smart city-based applications individually. However, industrialists and governments are hesitant to deploy smart city-based applications in real-time in a wider range due to high concern on data security and privacy as the raw and sensitive data is being transferred on an insecure internet. Moreover, since almost all smart city applications are life-critical systems, industrialists are hesitant to deploy these in real-time directly. To overcome these issues, DT and FL can be integrated and utilized for smart city-based life-critical applications.

The major contributions of this survey are summarized and listed below.

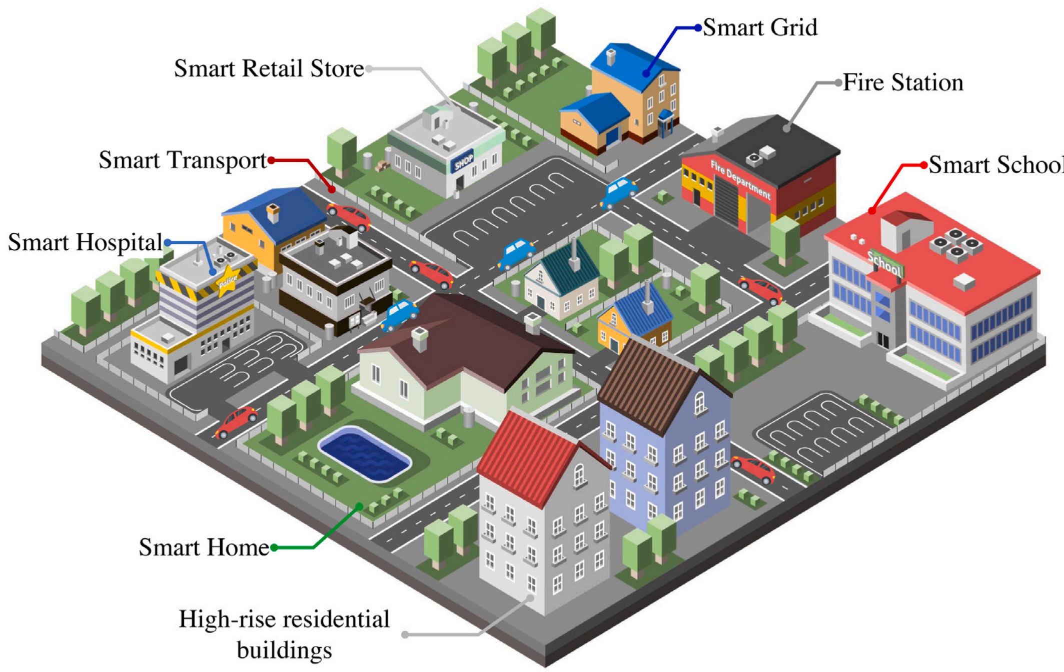

Fig. 1. Applications of Smart Cities.

Table 2
Summary of related surveys.

Reference	Theme of Work	DTs	FL	Smart Cities
Chukhno et al. (2020)	DTs in IoT edge networks	✓	×	×
Leng et al. (2021)	DTs in industrial monitoring	✓	×	×
Croatti et al. (2020)	DTs in healthcare	✓	×	×
Lim et al. (2020)	FL in mobile edge networks	×	✓	×
Xu et al. (2021)	FL in healthcare informatics	×	✓	×
Mylonas et al. (2021)	Smart city deployment using DTs	✓	×	✓
Dembski et al. (2020)	Models for urban planning using DTs	✓	×	✓
Zaballos et al. (2020)	Social IoT based smart campus DTs	✓	×	✓
Shahat et al. (2021)	Mapping of local vulnerabilities in smart city using 3D city models	✓	×	✓
White et al. (2021)	DT models for smart city feedback	✓	×	✓
Jiang et al. (2020)	Smart city sensing services	×	✓	✓
Zheng et al. (2021)	Smart city based applications of FL	×	✓	✓
Liu, Guo et al. (2021)	Trust management	×	✓	✓
Our survey	Integration of FL and DT for smart city based applications and its governance	✓	✓	✓

- A comprehensive survey on the integration of FL with DT for smart city applications is presented which is the first of its kind.
- Recent applications where FL is integrated with DT in several smart city applications like manufacturing, automobile, retail, smart city, 5G, Industrial IoT (IIoT) are illustrated.
- Various challenges that still persist and scope for future researchers are highlighted.

In this work, a systematic literature survey as discussed in Fuller et al. (2020), Sharma, Kosasih et al. (2020) are chosen for providing a comprehensive survey on integration of DT and FL for smart city applications, that include the following steps. Initially, we highlight the limitations of existing survey papers and highlight the motivations for using FL for DT in smart city-based applications. The next step is to search for relevant scientific/research articles on the application of FL for DTs in smart city applications. We have focused on high-quality articles that are peer-reviewed in relevant and reputed journals, conferences, symposiums, workshops, and books. The references reviewed in this work are obtained from high-reputed publishers such as IEEE, Elsevier, Wiley, Springer Nature, Taylor & Francis, and also well-known archival websites such as arXiv. Moreover, the following queries are used to find the related references, including “federated learning”, “digital twin”, “federated learning based digital twin”, "smart city applications“, ”smart city governance“ and ”federated learning digital twin project". In the next stage we have screened all the retrieved papers based on their titles. We have excluded the papers that have content of low-quality. Later, we identified the contributions of the paper by reading the abstract and searching the article for their contributions based on the relevant keywords. In the last stage, we have extracted the data that is related to our survey on the applications of FL for DT in smart city-based applications, services and its governance.

The rest of the paper is organized as follows. The fundamentals required for a better understanding of smart city, FL and DT technologies are discussed in Section 2. The recent smart city applications where FL and DT models are adopted are summarized in Section 3. A detailed analysis of the various challenges that are still open are discussed in Section 4 and finally, the paper is concluded with motivation for future scope in Section 5.

2. Fundamentals and motivations

The fundamentals of smart cities, DT, and FL, along with the motivation of integrating DT with FL for smart city applications are presented in this section.

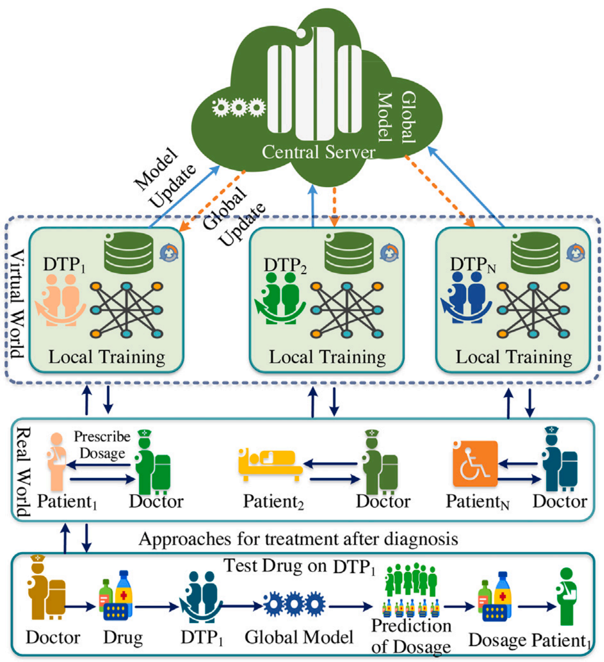

Fig. 2. Integration of FL and DT for Dosage Prescription in Healthcare 4.0.

2.1. Smart city

Smart city is developed to improve operational efficiency and provide a better quality of government service and citizen welfare by taking advantage of information and communication technology, which in turn enrich the quality of life for citizens and promote economic growth accordingly (Jararweh et al., 2020). The essential value is how smart technologies are used rather than simply how many technologies are available to optimize city functions. Basically, a standard smart city should have the characteristics as follows: infrastructure-based technologies, environmental initiatives, innovative and highly effective public transportation, progressive city development, and people able to have a comfortable life (Camero & Alba, 2019; Caragliu & Del Bo, 2019). In the technology aspect, smart city manipulates various software, user interfaces, and communication networks alongside the IoT to provide a secure connected solution for the public. IoT can be found in many digital devices as a network for connected devices to communicate and exchange data, from home appliances to vehicles and on-street sensors. Currently, many IoT devices use edge computing instead of cloud computing, which allows that only the most relevant data and selective information are transmitted over the communication networks (Feng et al., 2020; Jan et al., 2019). Besides, a security system should be implemented to protect and supervise the data transmission within a smart city network and between networks of different cities and prevent unauthorized access, or cyberattack to the IoT network (Alazab & Tang, 2019; Laufs, Borrion, & Bradford, 2020; Zhang et al., 2017). In addition to the IoT solutions, many innovative technologies are exploited for a smart city platform, for example, AI, cloud computing services, machine-to-machine communications, connected-autonomous driving, big data, and DTs.

Nowadays, smart-city techniques and applications have great potential to improve various urban quality-of-life aspects: safety, time, health, environment, connection, job, and cost of living. Some primary aspects are discussed as follows.

- *Safety*: Smart-city applications, such as smart surveillance and home security systems, can protect citizens from crime and improve other aspects of public safety. Smart systems can early detect incidents, optimize call centers, and recommend preliminary medical operations, while traffic-signal preemption can support emergency vehicles with an optimal driving path (Ji, Chen, Wei, & Su, 2021).
- *Time*: Smart-city technologies, such as connected autonomous driving and intelligent public transportation, can make daily commutes faster and less weary (Neil, Cosart, & Zampetti, 2020). In addition, IoT sensors and mobile apps using cloud/edge computing platforms can collect real-time information and transfer to the data center for processing, which allows optimizing traffic flows in rush hours and reducing road congestion besides other supportive applications like real-time navigation and smart parking.
- *Health*: Healthcare and medical data collected by IoT devices can be automatically analyzed to prevent, treat, and monitor chronic conditions at early stages. Remote-patient monitoring and diagnosis systems can help hospitals and medical centers reduce expense burden significantly (Enler, Pentek, & Adamko, 2020). In addition, telemedicine can provide clinical consultants with video conferences and solve doctor shortage problem in low-income cities.
- *Environment*: Natural environments are being damaged by urbanization, industrialization, and consumption. Several IoT-based applications are being developed for smart environments, such as smart water and energy management (Shamsuzzoha, Niemi, Piya, & Rutledge, 2021).

2.2. Digital twins

As the combination of a computational model and a real-world system, a DT allows customers and engineers to monitor, visualize, analyze, and optimize operational assets, processes, and systems by manipulating live IoT data besides providing real-time insights into performance and activity (Maddikunta et al., 2021; ODwyer, Pan, Charlesworth, Butler, & Shah, 2020; Tao & Qi, 2019). Because there is no universal framework and technology, DTs should be characterized by different design levels and development types to fit with various applications across a wide range of industrial domains.

2.2.1. Levels of digital twins

The operation of existing DTs can be categorized into five levels of sophistication: descriptive twin, informative twin, predictive twin, comprehensive twin, and autonomous twin.

- In level 1, the descriptive twin is a visual editable replica of assets, facilities, and products, where the kind of data for acquisition and the kind of information for extraction are specified.
- In level 2, the informative twin acquires sensory data from multiple modalities and provides insights into basic parameters/conditions to verify the system correctness.
- The predictive twin in level 3 integrates information technology and operational technology to identify complex patterns by applying advanced analytics and ML algorithms to big and noisy data. It is noted that early warnings/cautions can be offered by analyzing contextual data and learning from similar events or assets.
- With the comprehensive twin in level 4, several operating scenarios are simulated over physical-based, asset-based, and first-principle-based models. Moreover, some real-time simulations can be carried out for what-if questions, where the best practical actions for industry/product are recommended based on prescriptive analytics.
- In level 5, the autonomous twin adopts advanced predictive and prescriptive analytics with AI and ML for modeling and simulation of an entire plant/facility. Besides some minor specifications, such as three-dimensional visualization, high-speed computing power, integration of augmented reality and virtual reality, this twin is able to make decisions to correct issues or act on behalf of users autonomously.

Table 3
Digital Twin: Types and Use Cases.

	Use Case	Description
Part twins: Engineers can predict real-world behaviors of specific parts under a variety of operation scenarios. *Asset twins*: Product designers can verify operating behaviors with the estimation of failures and repairing time. *System twins*: Systems managers can monitor and analyze systems to maximize for efficiency and effectiveness. *Process twins*: Directors and officers can build manufacturing and business strategies with resource plan, supply chain, and asset maintenance.	*Healthcare*	DTs can provide healthcare providers visualization-based healthcare experience to optimize patient care, minimize cost, and increase performance. Use cases of healthcare can be categorized into two groups: enhancing operational efficiency of healthcare organizations and improving personalized care.
	Manufacturing	Applications of DTs are multifarious in the manufacturing industry. The high volume data generated by high-cost equipments in manufacturing facilitates the deployment of DTs. Some DTs applications are product development, design customization, predictive maintenance, aerospace, collaborative robotics, and self-driving car development.
	Smart Cities	With the support from DTs, an eco-economic and sustainable city can be revolutionized, where DTs can provide city managers real-time information and suitable solutions for several challenges, such as flooding, housing, water infrastructure, and transportation.
	Disaster Management	To deal with fires, floods, and droughts as the outcomes of the recent global temperature rise, DTs can support the construction of smart infrastructures, such as dams, utility delivery network, and emergency response strategy.
	Supply Chain Logistics	DTs are widely used in the supply chain/logistics industry with the following benefits: predicting the performance of packaging materials, improving shipment protection, and optimizing logistic network, and increasing operational performance of warehouse.
	Construction	With DTs, construction companies can supervise building in real time, which allows them to optimize efficiency and reduce cost. Data collected from DTs can be used to plan and design other buildings in future.
	Retail	Based on the shopping behaviors and customer personas, DTs can help retailers improve the customer experience. For example, retailers can recommend most suitable fashion clothing products to customers based on their DT models.

2.2.2. Types of DTs

Depending on the level of product magnification and the area of application, there are various development types of DTs, such as part twins, asset twins, system twins, and process twins.

- Represented as the smallest unit of a functioning module, part twins are the basic components of DTs.
- Asset twins, formed by incorporating multiple components, enable generating a massive amount of performance data to process and transform into meaningful insights.
- Based on the combination of different assets to conduct an entire functioning system, system twins provide perceptibility over the interaction between assets and suggest performance enhancements accordingly.
- As the macro level of product magnification, process twins describe the high-level interface between different systems or modules in an entire production facility. It should be noted that a system and process can be developed flexibly by coexisting different types of DTs.

With respect to every DTs type, the use cases are determined correspondingly in Table 3.

2.3. Federated learning

FL is currently being exploited in a broad spectrum of application areas: healthcare, autonomous driving, robotic, wireless communication, and supply chain finance (Pham, Dev, Maddikunta, Gadekallu, Huynh-The, et al., 2021; Sharma, Park et al., 2020). Depending on system abstractions and module deployments, existing FL systems can be categorized into four technical dimensions as follows.

- *Data partitioning*: Based on how the local data for learning ML models are distributed over the sample and feature spaces, this category can be divided into two sub-classes: horizontal FL and vertical FL. Recently, federated transfer learning aims to transfer knowledge across domains characterized by different feature spaces and sample representations (Li, Fan, Tse, & Lin, 2020).
- *ML model*: Classical ML algorithms can be grouped into supervised learning (so-called task-driven approach) and unsupervised learning (so-called data-driven approach). In supervised learning, the labeled data is learned for addressing classification and regression problems, whereas unsupervised learning algorithms can process unlabeled data for clustering and association rule learning problems (Pang, Guo et al., 2021).
- *Privacy mechanism*: Despite the extremely high privacy of local data in FL systems, the ML models are so sensitive to cyberattacks. Two major privacy strategies are usually adopted in recent FL systems: cryptography (e.g., homomorphic encryption and secure multi-party computation) and differential privacy (Wei et al., 2020).
- *Networking architecture*: Based on the network topology of model communications, this category can be divided into two subclasses: centralized FL and decentralized FL. In a centralized FL system, all clients transmit the trained parameters of local models to the central server to update the global model via parameter aggregation algorithms and then the computed global model is broadcast to all clients in a network for the next training iteration. In a decentralized FL system where all clients are connected over peer-to-peer communications, a client can transmit the model parameters trained on its local data to neighbor clients and receive model updates from them for parameter aggregation (Fadlullah & Kato, 2020).

2.4. Motivation for integrating FL and DT

The motivation behind integrating FL with DT is expressed in Table 4 and illustrated in Fig. 3. Even though DT has its own advantages, it lacks in maintaining data privacy since the data is communicated to the DT from the various sensor devices and physical entities. In FL, the privacy of data is preserved at the end-user environment by transmitting only the updates after local training in the edge device and the raw sensitive information is not communicated over the network.

Table 4
Comparative Analysis of Smart City DT with and without FL for better Governance.

Smart City DT with FL	Smart City DT without FL
Privacy-preserved communication among smart city DTs and also between smart city DT and edge devices in ehealth, intelligent transportation, etc.	Data Privacy is not maintained.
Data quality and integrity is improved as the data pre-processing is done at the edge device environment.	Data quality and integrity is minimal as the data is pre-processed in a centralized server.
Decision and prediction is faster due to a reduction in response time.	Since the training as well as decision making takes place in the centralized server, the response time is higher and hence decision as well as prediction is slower.
reduction in data breach since raw sensitive information is not transmitted via a network.	Vulnerable to data breach since sensitive data is transmitted across the network.
Improved latency and throughput.	Lower throughput and latency.
Communication cost is less.	Communication cost is high.
Less bandwidth is required.	High bandwidth is required.
Heterogeneous, huge and unstructured data can be handled easily.	Handling heterogeneous, huge and unstructured data is a challenge.

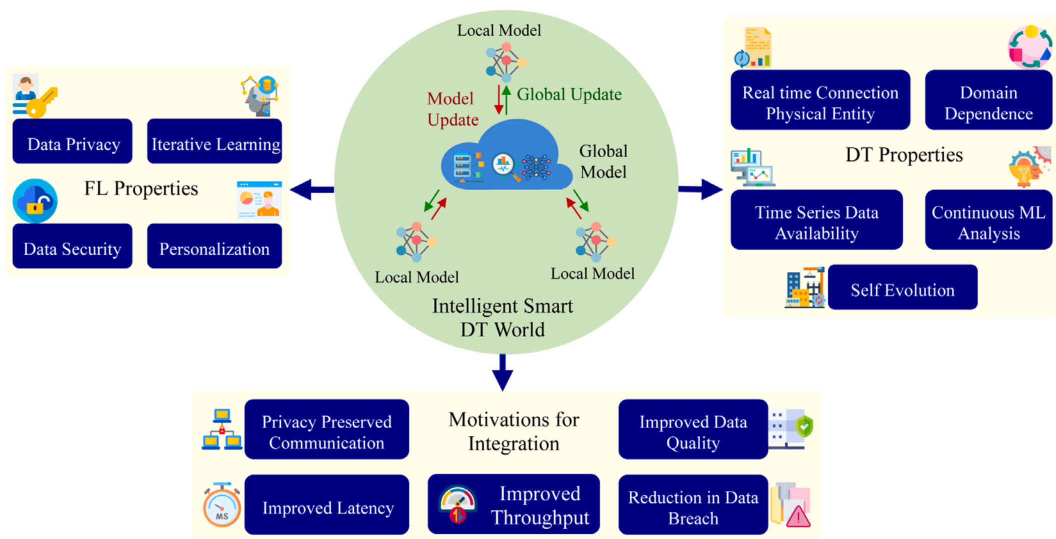

Fig. 3. Motivation for Integration of FL with DT.

Hence, when FL is integrated with DT, it would provide a privacy preserved communication among DTs and also between the DT and sensors. As DT technology is widely used in the healthcare and manufacturing industry, the response time of the system plays a vital role in executing any ML model. For instance, in trauma management, taking the decision and predicting the abnormalities in the least time is very essential. Other factors which motivated to integrate FL with DT are improving data quality and building a system with least response time. When FL is combined with DT, data pre-processing and training of models are done locally in the end devices which would improve the quality of data and reduce the response time. Also, by integrating FL with DT, the data breach can be reduced. Besides, certain cyberattacks like man-in-the-middle and denial of service can be overcome.

3. Core applications

Several researchers have proposed interesting solutions based on FL, DT to address several challenges in smart cities. Jiang et al. (2020) presented a survey on applications of FL for sensing in smart city to address the privacy and security of sensitive data in smart cities. Qolomany, Ahmad, Al-Fuqaha, and Qadir (2020) proposed a FL model based on particle swarm optimization for predicting the traffic in a smart city. Similarly, Farsi, Daneshkhah, Hosseinian-Far, Jahankhani, et al. (2020) have discussed the applications of digital twins in smart city. White et al. (2021) proposed to deploy a DT for allowing feedback by citizens on urban planning in a smart city. The proposed DT provides feedback on the proposed green spaces and buildings, simulating crowds and validating flooding in a smart city. In another interesting work, Francisco, Mohammadi, and Taylor (2020) presented a DT based solution for real-time energy management in a smart building. Rest of this section discusses the core applications of FL-based DT in smart city such as manufacturing, automobile, retail, smart cities, IIoT, and 5G and beyond. Table 5 summarizes the core applications of FL-based DT. Fig. 4 depicts the applications of FL-based DT.

3.1. FL-based DT in manufacturing

In recent years, a wide range of technologies has emerged that are important for the enhancement of industrial automation and manufacturing. While these technological advancements are changing the landscape of today's industry, DT has a significant impact on businesses for smart manufacturing. Using DT manufacturers can save time and money on designing, implementing, and certifying production processes. DT solves various challenges in the manufacturing process,

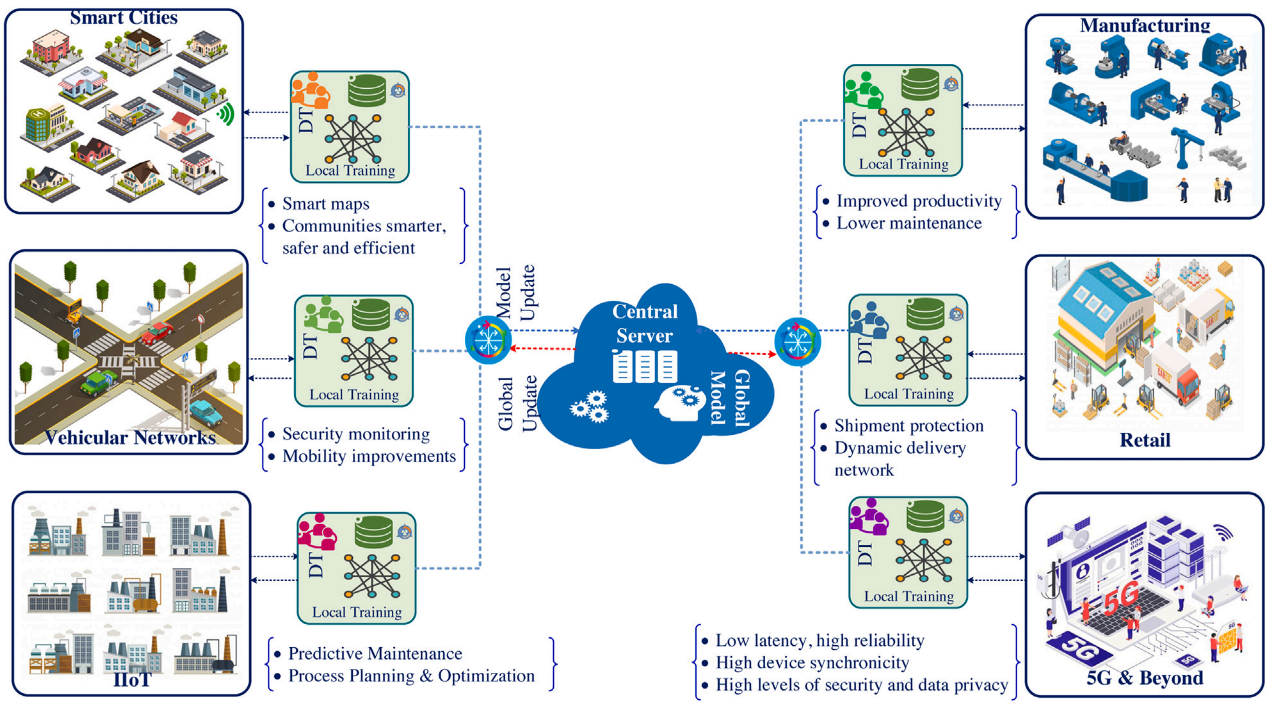

Fig. 4. Applications of FL for DTs..

such as lack of coordination, visibility of supply chain processes, and the ability to make faster decisions. DTs are utilized for decision-making in IIoT, which typically necessitates a massive amount of data for training devices to achieve better performance, while data collection raises security and privacy concerns. The combined challenges of privacy protection and big data present an opportunity to develop new technologies that collect and model data based on appropriate prerequisites (Gadekallu, Pham, Huynh-The et al., 2021). In Sun, Lei, Wang, Liu, and Zhang (2021), the authors proposed a DT architecture for IIoT applications, where DTs capture the features of manufacturing machinery. Deep-Q network was used to reduce the loss function of FL, as well as to optimize computing and communication energy. The authors developed an asynchronous FL architecture to minimize the straggler effect by clustering nodes and enhance learning efficiency. The results of the tests showed that the suggested model has a better energy consumption rate, a faster convergence rate, and a higher learning rate.

3.2. FL-based DT in automobile

DTs combine sensors, ML algorithms, and spatial network display software to create digital simulation portrayals of physical objects that provide quality services to intelligent automobile networks. DTs actively learn and upgrade from a variety of perspectives in order to recognize the operational requirements and position of physical objects, allowing them to predict upcoming events with high accuracy. DTs can predict the number of vehicles required by a country to fulfill its transportation needs, and can also assess traffic volume and routes. The driving states and environmental details of DT-enabled autonomous vehicles must be communicated to servers in order to update the DT framework. Furthermore, data transmission with minimal latency in such automobile networks with dynamic controlling systems and significant co-frequency interference is a challenging task. In addition, attackers may hack the information exchange between automobiles and servers, causing the vehicle driving control to be misled. It is necessary to address the issue of preserving DT operation in automobile networks.

3.3. FL-based DT in retail

In the advanced digital era, consumers are inspired by new innovative ideas, but the consumer goods and retail industries are failing to meet the demands of the consumers. The chain from design to decision to production to sale is time-consuming, risky, and cost-oriented. DT enables retailers to model their supply chains as a connected network. DT helps retailers in optimizing their supply chain, reducing time, and improving the consumer experience by establishing virtual models of a consumer. However, there are some risks associated with DT technologies, such as the leakage of sensitive information, lack of trust, and some practical limitations, such as latency and processing massive amounts of data. FL provides a privacy-aware model training approach that does not require information sharing. In FL, some retailers may upload untrustworthy data, causing the server to fail to aggregate the global model. As a result, finding trustworthy clients in FL is critical. In Kang et al. (2020), the authors proposed a reputation-based mechanism for selecting a trustworthy client. A decentralized consortium blockchain is deployed at the edge nodes to attain secure reputation management.

3.4. FL-based DT in smart healthcare

In FL, the clients will retain the training data locally and learn the shared model, that can help a smart city DT efficiently accumulate the insights from multiple sources. Pang, Huang et al. (2021) proposed integrating a smart city DT with FL to track the COVID-19 pandemic. The proposed framework allows the sharing of multiple cities DTs' status and local strategy quickly. The FL server manages multiple cities DTs' local updates and the global model is trained at several smart city DT systems till the FL model can correlate between several infection trends and response plans. This approach by the authors establishes a global view of the pandemic crisis management in the smart city by integrating FL with the city DT that can obtain the patterns and knowledge from multiple DTs. The proposed approach also helps in improving the DT of each city by the consolidation of data from other cities DTs without violating privacy preservation.

3.5. FL-based DT in iiot

IIoT is a complex network that interconnects several analytical sections, people at work, and industrial devices. Through the collaboration of the devices, automatic manufacturing applications from agriculture to automotive can be achieved, thus realizing Industry 4.0. The heterogeneity of the devices in IIoT makes it difficult to capture dynamic perception and intelligent decision making. DT can help in capturing the complex and dynamic IIoT environment. Real-time analytics and state-awareness of DT assists in decision making and execution. Decision making of the DT in IIoT is data-driven and is dependent on the large volumes of data that is distributed across several industrial devices. In real-time, data islands exist in IIoT and also there are privacy preservation issues; therefore, it is very difficult to integrate data that is spread across several devices. To address these issues, Sun et al. (2021) proposed a framework that is a fusion of DT, FL, edge computing and 6G for instant wireless connectivity of IIoT devices. The simulation results proved that the proposed model is better than the state-of-the-art in terms of energy-saving, convergence, and learning accuracy.

The work in Lu, Huang, Zhang, Maharjan, and Zhang (2021b) proposed a novel DT wireless network model, namely DTWN, for mitigating the long-distance and unreliable communication between the edge servers and end-users. To enable trust among the users, limited resources, and unreliable communication channels in IIoT, the authors proposed a blockchain integrated FL framework for defining the edge association problem in DTWN and for collaborative computing, that enhances the data privacy, improves security and reliability of the system. FL alienates the privacy concerns for learning and distributed data processing in wireless networks.

3.6. FL-based DT in 5G and beyond

Creating unified networks with intelligent connections is a key factor in 5G and beyond that will be built into distributed network (Dighriri, Lee, & Baker, 2018; Ding, Zhu, Alazab, Li, & Yu, 2020). The network dynamics and client heterogeneity affect the context awareness and the data collection. The work in Sun, Xu, Wang, Zhang, and Zhang (2020) proposed a dynamic architecture based on DT for air–space–ground networks, where the DT is supposed to capture dynamic characteristics of networks. A drone is used in this proposed architecture to aggregate the data and the ground clients such as smartphones, and vehicles are used for training the FL model collaboratively. FL is used for privacy preservation and to deal with the information islands in heterogeneous networks.

4. Challenges and future directions

Even though DT has been widely used in Industry 4.0 for accelerating risk assessment, predictive maintenance, remote monitoring and better decision making, there are some issues faced while using this technology. Fig. 5 depicts various challenges and possible solutions in literature and the same is discussed in this section as shown in Table 6, followed by future directions.

4.1. Data privacy and security

Most of the data are collected from the edge devices in DT technology. Actually, these are highly prone to attacks and vulnerable to various threats like denial of service and SQL injection. It is evident that DT uses vast amount of data that poses a risk of exposing sensitive data. There is a chance that attacks can happen either in the edge devices or while communicating the data for training the models.

Security and privacy issues have become major issues in the implementation of smart city. However, traditional security and privacy algorithms cannot be directly applicable to existing intelligent smart city applications because of their heterogeneity and dynamic features (Ismagilova, Hughes, Rana, & Dwivedi, 2020). Smart cities designed with IoT botnets are more vulnerable to DDoS attacks. Therefore, there should be a novel defense mechanism to overcome these challenges. Driverless cars in autonomous vehicles are exposed to remote attacks like applying brakes, shutting down engine and controlling the steering (Pham & Xiong, 2021). Virtual reality devices in smart city are used by various departments like health, infrastructure and transport systems. Data communication between these systems may lead to privacy leakage threats. AI-based smart systems also play a major role in security breaches like smart home and smart machines (Haney, Furman, & Acar, 2020). There is a high probability of hacking the personal information either from the manufacturer of smart product or from the service providers.

Solution: To overcome the security issue, access privileges can be defined, data encryption algorithms can be applied, addressing the device vulnerability and conducting regular security audits. Replica of DT can reside on each edge device which trains the local model and the result of each DT should be integrated to train the global model. Applying FL on DT would ensure data privacy and security as they communicate only the updates of the model or the result and not the data. By this approach, hacking of data while communicating in the network can be avoided. User data can also be protected using privacy preservation algorithms on model updates (Cheng, Liu, Chen, & Yang, 2020)

4.2. Data quality

DT models collect the data from sensors that communicate over unreliable networks. The quality of data should be good for training the AI models. If the data has noisy and outlier information, it may produce an inaccurate result (Gupta, Panagiotopoulos, & Bowen, 2020). Smart city involves the integration of information from various systems like traffic, city planning, infrastructure and smart communication. While integrating the data from all the sources, if the data is not pre-processed, it may result in incorrect analysis and decision-making (Reddy et al., 2020). Noise that exists in the data results in inaccurate solutions.

Solution: Noisy and outlier data should be filtered in the initial stage to maximize the accuracy of the output. Horizontal FL can be used to pre-process the data in the DT present at the end-user. Traditional approaches collect and integrate the data from all the sensors and then pre-process the whole data, whereas in DT with FL approach, data is pre-processed in each replica of DT and trained using the global models.

4.3. Data sharing

Sharing of data involves both external and internal sharing of information. Internal data sharing refers to the fetching of data from various departments within an organization, whereas external sharing takes place between stakeholders across the supply chain. Even though DT provides high scalability by increasing the number of digital copies for any dynamic process, data sharing becomes a hurdle due to security problems and data breaches. In smart city applications, data sharing happens between IoT devices and the cloud server (Rubí & de Lira Gondim, 2021). Data exchange between the smart application and devices can be easily tampered during the transmission process. Firewalls and security protocols can be implemented in the edge devices.

Solution: Data sharing can happen efficiently by integrating FL with DT. Instead of sharing the whole information among the DTs, it would be better if the required information alone can be sliced and shared. To achieve this, vertical FL can be applied to get the details with respect to specific feature. Horizontal FL can be applied if the data related to specific entities with respect to a particular feature is required.

Table 5
Summary of Core Applications of FL-based DT.

Core Applications	Challenges	FL–DT Advantages	Solutions
Manufacturing	1. Poor energy consumption rate. 2. Slow convergence rate. 3. Poor learning rate.	1. Improved productivity. 2. Lower maintenance.	DTs capture the features of manufacturing machinery. Deep-Q network reduces the loss function of FL, as well as to optimize computing and communication energy. FL architecture minimize the straggler effect by clustering nodes and enhance learning efficiency.
Automobile	1. Predicting the number of vehicles. 2. Assessing traffic volume and routes. 3. Hacking the information exchange between automobiles and servers.	1. Security monitoring. 2. Mobility improvements. 3. Predict upcoming events with high accuracy.	DTs with FL can predict the number of vehicles required by a country to fulfill its transportation needs, and can assess traffic volume and routes. The driving states and environmental details of FL-based DT-enabled autonomous vehicles communicate to servers to update the FL-based DT framework. Further, data transmission with minimal latency in automobile networks with dynamic controlling systems and significant co-frequency interference is minimized. Protect the attackers from hacking information exchange between automobiles and servers, causing the vehicle driving control to be misled.
Retail	1. The chain from design to decision to production to sale is time-consuming, risky, and cost-oriented. 2. Leakage of sensitive information, lack of trust, and some practical limitations, e.g., latency and data processing.	1. Shipment protection. 2. Dynamic delivery network.	DT enables retailers to model their supply chains as a connected network. DT helps retailers in optimizing their supply chain, reducing time, and improving the consumer experience by establishing virtual models of a consumer. In FL, some retailers may upload untrustworthy data, causing the server to fail to aggregate the global model. As a result, finding trustworthy clients in FL is critical. A reputation-based mechanism is used for selecting a trustworthy client. A decentralized consortium blockchain is deployed at the edge nodes to attain secure reputation management.
Smart Healthcare	1. Leakage of sensitive information. 2. Poor Prediction rate.	1. Better accuracy rate. 2. Improves the consolidation of secure data.	DT with FL helps to track COVID-19, sharing of multiple cities DTs' status and local strategy quickly. The FL server manages multiple cities DTs' local updates and the global model is trained at several smart city DT systems till the FL model can correlate between several infection trends and response plans. This approach establishes a global view of the pandemic crisis management in the smart city by integrating FL with the city DT that can obtain the patterns and knowledge from multiple DTs. Helps in improving the DT of each city by the consolidation of data from other cities DTs without violating privacy preservation.
Industrial IoT	1. Difficult to capture dynamic perception. 2. Poor intelligent decision making.	1. Capturing complex and dynamic IIoT environment. 2. Real-time analytics and state-awareness in decision making and execution.	Decision making of the FL-based DT in IIoT is data-driven and is dependent on the large volumes of data that is distributed across several industrial devices. In real-time, data islands exist in IIoT and addresses the privacy preservation issues that makes it very difficult to integrate data that is spread across several devices.
5G and Beyond	1. Poor Latency. 2. Poor privacy preservation to deal with the information islands in heterogeneous networks.	1. Low latency. 2. High reliability. 3. High device synchronicity. 4. High security and data privacy.	FL-based DT for air–space–ground networks capture dynamic characteristics of networks. A drone can be used to aggregate the data and the ground clients such as smartphones, and vehicles are used for training the FL model collaboratively. FL is used for privacy preservation and to deal with the information islands in heterogeneous networks.

4.4. User interaction

Human interaction with DT models play a major issue in digital process. Particularly, if a human wants to actively participate in the decision making process, a DT system needs to wait till it receives the human input. Data from all traffic sensors in smart city are integrated and updated to the cloud. Data analytics are performed in cloud server and then it is communicated to the smart devices. This way of transmitting data from device to cloud and vice versa would take more time for decision-making process (Chen, Wei, Chen, Wang, & Zhou, 2020).

Solution: In FL, local data is trained locally (Lu, Huang, Zhang, Maharjan, & Zhang, 2021a) and only the updates are shared to the cloud to train the global model. This would facilitate human intervention more easier because decision making process can be initiated from the DTs rather than waiting till the global model is generated.

4.5. Data integration

Integrating the information from all domains is a complex task as everyone should understand the specific requirements of the concerned domains. Each and every phase has its own parameters, conditions, and optimization concepts. So it is essential to know the previous and future activities of the process to achieve the flow of information smoothly.

Sometimes decisions in smart city applications are made by combining information from different domains and from various sensors. While integration, data heterogeneity, data traffic, data scalability must be handled dynamically. AI techniques (Tan, Yu, Ming, Chen, & Srivastava, 2021) can be applied to handle the complex integration of data.

Solution: In general, integrity issues can be solved using user access controls, version control, and error detection software. But using FL with DTs can solve the integrity issues in a secured manner. When the results from all the DTs are integrated data breach is avoided as it integrates only the updates from the model and not the original data.

4.6. Information flow

Integrating data from different domain in DT leads to flood of information. So the flow of information should be streamlined and designed efficiently. Controlling the information flow will ensure that the acquired information is available to the user and the noisy data is eliminated. Users from different teams can access the correct data and simulated results are interpreted, which lead to secure decisions. Flow of information from various sensors and smart devices in each smart application results in flooding of flow of information. Streamlining of data is very necessary to avoid data traffic.

Solution: FL with DTs provides two solutions to avoid flood of information. First, communication of model updates (Yang, Liu, Chen, & Tong, 2019) would eliminate overflow of information. Secondly, usage of transfer FL would provide a solution. Model updates from specific layers of the local model can be sent to the server instead of sending updates from all the layers.

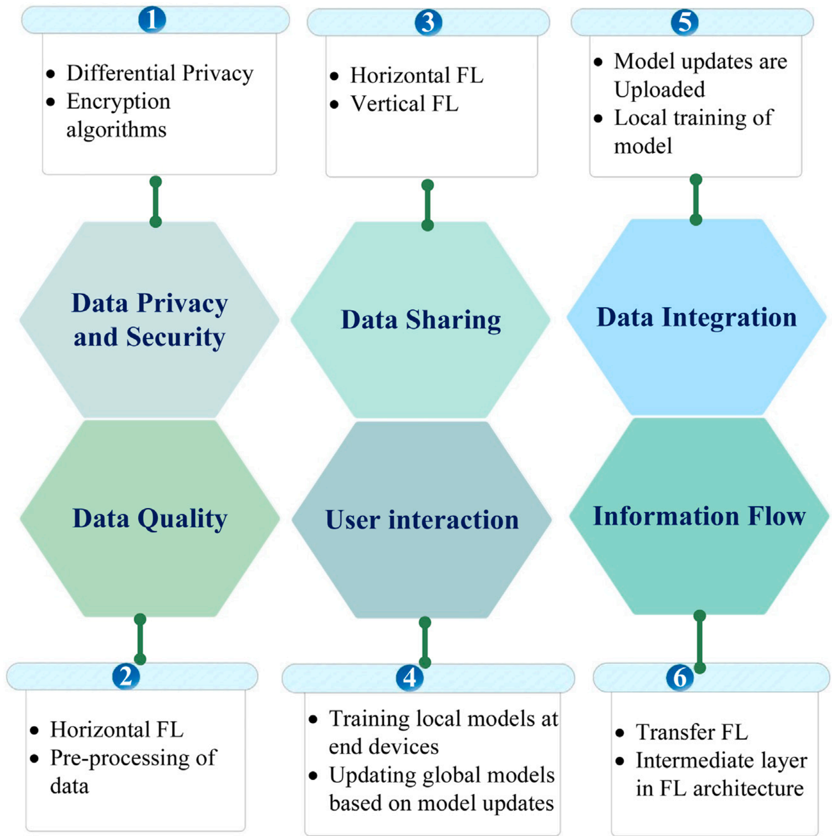

Fig. 5. Integration of FL with DT: Challenges and Solutions..

4.7. Explainability/justification/interpretability

Due to the blackbox nature of ML algorithms, the predictions/ classifications of FL on the data generated from the DTs may lead to a significant challenge in reliability and adaptability of the FL. The lack of justification on the prediction/classification algorithms of ML algorithms is a serious bottleneck in the adaptability of FL in DTs for several mission critical applications in smart cities.

Solution: Explainable AI (XAI) algorithms provide justification/ interpretability/explainability to the ML algorithms (Wang, Qureshi et al., 2021). Hence adapting XAI algorithms in FL for DTs for smart city applications increase the reliability and trustability of the FL models.

4.8. Training the team

Users of DT technology must be trained to adapt to the latest and new technical capabilities.

Solution: Organization should ensure that human resources and models are well trained and has the required skillset to handle the DT models.

4.9. Future directions

From our findings, we summarize that the DT concept is already very impressive and has shown a high impact in various domains in smart city. The technology is also widespread in real-time industrial applications. In future, the researchers should adopt the technology in other sensitive domains like autonomous vehicles, aircraft and health-care for implementing smart city. Security and privacy issues are a major challenge in real-time implementation and deployment. Researchers can further focus on developing frameworks for integrating DT and FL for adoption in real-time sensitive applications. Also, developing standards and frameworks to suit 5G and beyond networks is a further scope. In the near future, there is a high possibility of adoption of the DT technology in all domains and sensitive applications, which can impact the daily life of people in the real-world.

4.9.1. Blockchain

Decentralized feature of blockchain-based secured technology would enhance the reliability and efficiency of the system. It stores information in the form of digital ledgers and reduces the complexity of storing large datasets in single machine (Gadekallu, Pham, Nguyen et al., 2022; Singh, Sharma et al., 2020; Wang, Qiu et al., 2021). Hence, blockchain can improve the efficiency of smart cities by high transparency and traceability. Information is stored in multiple devices for efficient supply management and data availability. Blockchain technology can be applied in various smart city deployments like retail, finance, banking, e-governance, education, infrastructure and transportation.

4.9.2. Industry 5.0

Smart cities under Industry 5.0 would design strategies and policies over IoT devices and support dynamic, diversified and flexible processes. The goal of Industry 5.0 is to allow humans and machines to cooperate that would result in mass personalization (Maddikunta et al., 2021). Industry 5.0 is the symmetric approach to innovate the smart ecosystem with more automation and innovation using the latest technologies. It would also solve societal issues by designing robust and sustainable innovations.

4.9.3. Quantum digital twins

Quantum computing produces more benefits than classical computing. As traditional computing can pose only binary states, quantum bits known as qubits can superposition multiple states. Modeling vast range of possible state by increasing exponentially with number of qubits is known as quantum parallelism. Quantum computers can also scan the information faster than traditional databases. It will be faster

Table 6
Challenges and Solutions of DT with FL in Smart City.

Challenges	Challenges faced in smart city	Solution
Security and privacy	1. DDoS attacks in IoT botnets and virtual reality devices 2. SQL injection attack in driverless cars in autonomous vehicles and AI based smart systems	1. Updates on the model only are communicated in the network using FL technology 2. Replica of DT can reside in each edge device 3. Privacy preservation algorithms on each DT
Data quality	1. Noisy data generated from smart devices 2. Integration of heterogeneous information from various departments	1. Horizontal FL can be used to preprocess the data 2. Each replica of DT is preprocessed in edge devices
Data sharing	1. Security threats in data communication 2. Tampering of data between the devices and cloud server	1. Firewalls and security protocols 2. Horizontal and vertical FL can be used
User interaction	1. Delayed decision-making process in edge devices 2. Less response time from the smart device	1. Local Training of data in FL 2. Decision-making can be initiated in DT rather than in cloud server
Data integration	1. Integration of data from various applications 2. Dynamic handling of complex data integrated from different smart devices	1. Results of all DTs can be combined to achieve secure integration 2. AI can be applied in local model present in edge devices rather than in the global model
Information flow	1. Combining data from different domain DT leads to flood of information 2. Access time of information increases with data traffic	1. Transfer FL can be used 2. Layer wise model updates are transferred

for complex computational tasks that involve multiple dimension of information. Integrating Quantum with Digital Twins would not just reflect the reality but allow us to allow to analyze the consequence of decisions. Quantum DT allows transport operators to provide us with both the likelihood and impact of disruption. So the main goal of quantum is not just to mirror but to manage and extract more from the system of systems.

4.9.4. Cognitive digital twins

Integrating cognitive artificial intelligence with digital twin enhance and improve the productivity and development process faster and efficient. Cognitive DT examines the current system or process and recommends the current structure. A cognitive twin is an entity that process the thought, acquire input knowledge and solves the problem by itself and makes decisions on its own. Artificial intelligence has the ability to solve problems and predict the twin using the past information and control its twin using cognitive function. It represents the next evolution of DT technology which will effectively handle unforeseen situations. It combines human knowledge and digital twin models in order to react better and make perfect decisions in all situations without any interventions.

In future, the researchers should adopt the technology in other sensitive domains like autonomous vehicles, aircraft and healthcare for implementing smart city. Security and privacy issues are a major challenge in real-time implementation and deployment. Researchers can further focus on developing frameworks for integrating DT and FL for adoption in real-time sensitive applications. Also, developing standards and frameworks to suit 5G and beyond networks is a further scope. In the near future, there is a high possibility of adoption of the DT technology in all domains and sensitive applications, which can impact the daily life of people in the real-world.

5. Conclusion

In the previous decade, the continuous advancements in AI-based techniques, IoT, and FL have encouraged the utilization of DT in various domains. Numerous DTs have already been developed and are successfully being utilized in various sectors like manufacturing, automobiles, retail, smart cities, IIoT, and 5G and beyond. In this article, a survey of integrating FL with DT for ease of governance in smart cities is presented. The paper starts by highlighting the various characteristics of DTs and how it is different from the already developed similar technologies. Next, the fundamentals of smart city, DT and FL are discussed. Later, we have highlighted the various smart city-based applications where these technologies are integrated for adoption so that the governance of the deployed smart city becomes less complex and better. Finally, various challenges that still persist and act as a hurdle in the utilization of this integration in real-time and life-critical applications of smart cities are discussed along with their potential solutions.

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.

References

Alazab, M., & Tang, M. (2019). *Deep learning applications for cyber security*. Springer.
Björnsson, B., Borrebaeck, C., Elander, N., Gasslander, T., Gawel, D. R., Gustafsson, M., et al. (2020). Digital twins to personalize medicine. *Genome Medicine*, *12*(1), 1–4.
Camero, A., & Alba, E. (2019). Smart city and information technology: A review. *Cities*, *93*, 84–94.
Caragliu, A., & Del Bo, C. F. (2019). Smart innovative cities: The impact of smart city policies on urban innovation. *Technological Forecasting And Social Change*, *142*, 373–383.
Chen, M., Wei, X., Chen, J., Wang, L., & Zhou, L. (2020). Integration and provision for city public service in smart city cloud union: Architecture and analysis. *IEEE Wireless Communications*, *27*(2), 148–154.
Cheng, Y., Liu, Y., Chen, T., & Yang, Q. (2020). Federated learning for privacy-preserving AI. *Communications Of The ACM*, *63*(12), 33–36.
Chukhno, O., Chukhno, N., Araniti, G., Campolo, C., Iera, A., & Molinaro, A. (2020). Optimal placement of social digital twins in edge IoT networks. *Sensors*, *20*(21), 6181.
Croatti, A., Gabellini, M., Montagna, S., & Ricci, A. (2020). On the integration of agents and digital twins in healthcare. *Journal Of Medical Systems*, *44*(9), 1–8.
Dembski, F., Wössner, U., Letzgus, M., Ruddat, M., & Yamu, C. (2020). Urban digital twins for smart cities and citizens: The case study of herrenberg, Germany. *Sustainability*, *12*(6), 2307.
Dighriri, M., Lee, G. M., & Baker, T. (2018). Measurement and classification of smart systems data traffic over 5G mobile networks. In *Technology For Smart Futures* (pp. 195–217). Springer.
Ding, F., Zhu, G., Alazab, M., Li, X., & Yu, K. (2020). Deep-learning-empowered digital forensics for edge consumer electronics in 5G HetNets. *IEEE Consumer Electronics Magazine*.
Enler, E., Pentek, I., & Adamko, A. (2020). Healthcare framework for smarter cities with bio-sensory data. In *2020 11th IEEE international conference on cognitive infocommunications* (pp. 000337–000342). IEEE.
Fadlullah, Z. M., & Kato, N. (2020). HCP: Heterogeneous computing platform for federated learning based collaborative content caching towards 6G networks. *IEEE Transactions On Emerging Topics In Computing*.
Fan, C., Jiang, Y., & Mostafavi, A. (2020). Social sensing in disaster city digital twin: Integrated textual–visual–geo framework for situational awareness during built environment disruptions. *Journal Of Management In Engineering*, *36*(3), Article 04020002.

Farsi, M., Daneshkhah, A., Hosseinian-Far, A., Jahankhani, H., et al. (2020). Digital twin technologies and smart cities. Springer.
Feng, C., Yu, K., Aloqaily, M., Alazab, M., Lv, Z., & Mumtaz, S. (2020). Attribute-based encryption with parallel outsourced decryption for edge intelligent IoV. *IEEE Transactions On Vehicular Technology*, *69*(11), 13784–13795.
Francisco, A., Mohammadi, N., & Taylor, J. E. (2020). Smart city digital twin–enabled energy management: Toward real-time urban building energy benchmarking. *Journal Of Management In Engineering*, *36*(2), Article 04019045.
Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin: Enabling technologies, challenges and open research. *IEEE Access*, *8*, 108952–108971.
Gadekallu, T. R., Pham, Q.-V., Huynh-The, T., Bhattacharya, S., Maddikunta, P. K. R., & Liyanage, M. (2021). Federated learning for big data: A survey on opportunities, applications, and future directions. arXiv preprint arXiv:2110.04160.
Gadekallu, T. R., Pham, Q.-V., Nguyen, D. C., Maddikunta, P. K. R., Deepa, N., Prabadevi, B., et al. (2022). Blockchain for edge of things: Applications, opportunities, and challenges. *IEEE Internet Of Things Journal*, *9*(2), 964–988.
Gupta, A., Panagiotopoulos, P., & Bowen, F. (2020). An orchestration approach to smart city data ecosystems. *Technological Forecasting And Social Change*, *153*, Article 119929.
Hakak, S., Khan, W. Z., Gilkar, G. A., Imran, M., & Guizani, N. (2020). Securing smart cities through blockchain technology: Architecture, requirements, and challenges. *IEEE Network*, *34*(1), 8–14.
Haney, J. M., Furman, S. M., & Acar, Y. (2020). Smart home security and privacy mitigations: Consumer perceptions, practices, and challenges. In *International conference on human-computer interaction* (pp. 393–411). Springer.
He, C., Liu, Z., Wu, J., Pan, X., Fang, Z., Li, J., et al. (2021). Future global urban water scarcity and potential solutions. *Nature Communications*, *12*(1), 1–11.
Ismagilova, E., Hughes, L., Rana, N. P., & Dwivedi, Y. K. (2020). Security, privacy and risks within smart cities: Literature review and development of a smart city interaction framework. *Information Systems Frontiers*, 1–22.
Jan, M. A., Zhang, W., Usman, M., Tan, Z., Khan, F., & Luo, E. (2019). SmartEdge: An end-to-end encryption framework for an edge-enabled smart city application. *Journal Of Network And Computer Applications*, *137*, 1–10.
Jararweh, Y., Otoum, S., & Al Ridhawi, I. (2020). Trustworthy and sustainable smart city services at the edge. *Sustainable Cities And Society*, *62*, Article 102394.
Ji, T., Chen, J.-H., Wei, H.-H., & Su, Y.-C. (2021). Towards people-centric smart city development: Investigating the citizens preferences and perceptions about smart-city services in Taiwan. *Sustainable Cities And Society*, *67*, Article 102691.
Jiang, J. C., Kantarci, B., Oktug, S., & Soyata, T. (2020). Federated learning in smart city sensing: Challenges and opportunities. *Sensors*, *20*(21), 6230.
Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the digital twin: A systematic literature review. *CIRP Journal Of Manufacturing Science And Technology*, *29*, 36–52.
Kang, J., Xiong, Z., Niyato, D., Zou, Y., Zhang, Y., & Guizani, M. (2020). Reliable federated learning for mobile networks. *IEEE Wireless Communications*, *27*(2), 72–80.
Khatoon, S., Rahman, S. M. M., Alrubaian, M., & Alamri, A. (2019). Privacy-preserved, provable secure, mutually authenticated key agreement protocol for healthcare in a smart city environment. *IEEE Access*, *7*, 47962–47971.
Kumar, P., Kumar, R., Srivastava, G., Gupta, G. P., Tripathi, R., Gadekallu, T. R., et al. (2021). PPSF: A privacy-preserving and secure framework using blockchain-based machine-learning for IoT-driven smart cities. *IEEE Transactions On Network Science And Engineering*.
Laufs, J., Borrion, H., & Bradford, B. (2020). Security and the smart city: A systematic review. *Sustainable Cities And Society*, *55*, Article 102023.
Leng, J., Wang, D., Shen, W., Li, X., Liu, Q., & Chen, X. (2021). Digital twins-based smart manufacturing system design in industry 4.0: A review. *Journal Of Manufacturing Systems*, *60*, 119–137.
Li, L., Fan, Y., Tse, M., & Lin, K.-Y. (2020). A review of applications in federated learning. *Computers & Industrial Engineering*, Article 106854.
Li, G., Zhang, X., Mirzaei, P. A., Zhang, J., & Zhao, Z. (2018). Urban heat island effect of a typical valley city in China: responds to the global warming and rapid urbanization. *Sustainable Cities And Society*, *38*, 736–745.
Lim, W. Y. B., Luong, N. C., Hoang, D. T., Jiao, Y., Liang, Y.-C., Yang, Q., et al. (2020). Federated learning in mobile edge networks: A comprehensive survey. *IEEE Communications Surveys & Tutorials*, *22*(3), 2031–2063.
Liu, M., Fang, S., Dong, H., & Xu, C. (2021). Review of digital twin about concepts, technologies, and industrial applications. *Journal Of Manufacturing Systems*, *58*, 346–361.
Liu, C., Guo, S., Guo, S., Yan, Y., Qiu, X., & Zhang, S. (2021). LTSM: Lightweight and trusted sharing mechanism of IoT data in smart city. *IEEE Internet Of Things Journal*.
Lu, Y., Huang, X., Zhang, K., Maharjan, S., & Zhang, Y. (2021a). Communication-efficient federated learning and permissioned blockchain for digital twin edge networks. *IEEE Internet Of Things Journal*, *8*(4), 2276–2288. http://dx.doi.org/10.1109/JIOT.2020.3015772.
Lu, Y., Huang, X., Zhang, K., Maharjan, S., & Zhang, Y. (2021b). Low-latency federated learning and blockchain for edge association in digital twin empowered 6G networks. *IEEE Transactions On Industrial Informatics*, *17*(7), 5098–5107. http://dx.doi.org/10.1109/TII.2020.3017668.
Maddikunta, P. K. R., Pham, Q.-V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T. R., et al. (2021). Industry 5.0: a survey on enabling technologies and potential applications. *Journal Of Industrial Information Integration*, Article 100257.
Mothukuri, V., Khare, P., Parizi, R. M., Pouriyeh, S., Dehghantanha, A., & Srivastava, G. (2021). Federated learning-based anomaly detection for IoT security attacks. *IEEE Internet Of Things Journal*.
Mothukuri, V., Parizi, R. M., Pouriyeh, S., Huang, Y., Dehghantanha, A., & Srivastava, G. (2021). A survey on security and privacy of federated learning. *Future Generation Computer Systems*, *115*, 619–640.
Mylonas, G., Kalogeras, A., Kalogeras, G., Anagnostopoulos, C., Alexakos, C., & Muñoz, L. (2021). Digital twins from smart manufacturing to smart cities: A survey. *IEEE Access*.
Neil, J., Cosart, L., & Zampetti, G. (2020). Precise timing for vehicle navigation in the smart city: an overview. *IEEE Communications Magazine*, *58*(4), 54–59.
Niknam, S., Dhillon, H. S., & Reed, J. H. (2020). Federated learning for wireless communications: Motivation, opportunities, and challenges. *IEEE Communications Magazine*, *58*(6), 46–51.
OBrien, P., Pike, A., & Tomaney, J. (2019). Governing the ungovernable? Financialisation and the governance of transport infrastructure in the London global city-region. *Progress In Planning*, *132*, Article 100422.
ODwyer, E., Pan, I., Charlesworth, R., Butler, S., & Shah, N. (2020). Integration of an energy management tool and digital twin for coordination and control of multi-vector smart energy systems. *Sustainable Cities And Society*, *62*, Article 102412.
Pang, Z., Guo, J., Sun, W., Xiao, Y., & Yu, M. (2021). Cross-domain person re-identification by hybrid supervised and unsupervised learning. *Applied Intelligence: The International Journal of Artificial Intelligence, Neural Networks, and Complex Problem-Solving Technologies*, 1–15.
Pang, J., Huang, Y., Xie, Z., Li, J., & Cai, Z. (2021). Collaborative city digital twin for the COVID-19 pandemic: A federated learning solution. *Tsinghua Science And Technology*, *26*(5), 759–771.
Pham, Q.-V., Dev, K., Maddikunta, P. K. R., Gadekallu, T. R., Huynh-The, T., et al. (2021). Fusion of federated learning and industrial internet of things: a survey. arXiv preprint arXiv:2101.00798.
Pham, M., & Xiong, K. (2021). A survey on security attacks and defense techniques for connected and autonomous vehicles. *Computers & Security*, Article 102269.
Qolomany, B., Ahmad, K., Al-Fuqaha, A., & Qadir, J. (2020). Particle swarm optimized federated learning for industrial IoT and smart city services. In *GLOBECOM 2020-2020 IEEE global communications conference* (pp. 1–6). IEEE.
Rasheed, A., San, O., & Kvamsdal, T. (2020). Digital twin: Values, challenges and enablers from a modeling perspective. *IEEE Access*, *8*, 21980–22012.
Reddy, G. T., Reddy, M. P. K., Lakshmanna, K., Kaluri, R., Rajput, D. S., Srivastava, G., et al. (2020). Analysis of dimensionality reduction techniques on big data. *IEEE Access*, *8*, 54776–54788.
Rubí, J. N. S., & de Lira Gondim, P. R. (2021). IoT-based platform for environment data sharing in smart cities. *International Journal Of Communication Systems*, *34*(2), Article e4515.
Shahat, E., Hyun, C. T., & Yeom, C. (2021). City digital twin potentials: A review and research agenda. *Sustainability*, *13*(6), 3386.
Shamsuzzoha, A., Niemi, J., Piya, S., & Rutledge, K. (2021). Smart city for sustainable environment: A comparison of participatory strategies from helsinki, Singapore and London. *Cities*, *114*, Article 103194.
Sharma, A., Kosasih, E., Zhang, J., Brintrup, A., & Calinescu, A. (2020). Digital twins: State of the art theory and practice, challenges, and open research questions. arXiv preprint arXiv:2011.02833.
Sharma, P. K., Park, J. H., & Cho, K. (2020). Blockchain and federated learning-based distributed computing defence framework for sustainable society. *Sustainable Cities And Society*, *59*, Article 102220.
Shirowzhan, S., Tan, W., & Sepasgozar, S. M. (2020). *Digital twin and cybergis for improving connectivity and measuring the impact of infrastructure construction planning in smart cities*. Multidisciplinary Digital Publishing Institute.
Singh, S. K., Jeong, Y.-S., & Park, J. H. (2020). A deep learning-based IoT-oriented infrastructure for secure smart city. *Sustainable Cities And Society*, *60*, Article 102252.
Singh, S., Sharma, P. K., Yoon, B., Shojafar, M., Cho, G. H., & Ra, I.-H. (2020). Convergence of blockchain and artificial intelligence in IoT network for the sustainable smart city. *Sustainable Cities And Society*, *63*, Article 102364.
Sun, W., Lei, S., Wang, L., Liu, Z., & Zhang, Y. (2021). Adaptive federated learning and digital twin for industrial internet of things. *IEEE Transactions On Industrial Informatics*, *17*(8), 5605–5614. http://dx.doi.org/10.1109/TII.2020.3034674.
Sun, W., Xu, N., Wang, L., Zhang, H., & Zhang, Y. (2020). Dynamic digital twin and federated learning with incentives for air-ground networks. *IEEE Transactions On Network Science And Engineering*.
Tan, L., Yu, K., Ming, F., Chen, X., & Srivastava, G. (2021). Secure and resilient artificial intelligence of things: a HoneyNet approach for threat detection and situational awareness. *IEEE Consumer Electronics Magazine*.
Tao, F., & Qi, Q. (2019). *Make more digital twins*. Nature Publishing Group.
Tao, F., Zhang, H., Liu, A., & Nee, A. Y. (2018). Digital twin in industry: State-of-the-art. *IEEE Transactions On Industrial Informatics*, *15*(4), 2405–2415.
Wang, W., Qiu, C., Yin, Z., Srivastava, G., Gadekallu, T. R., Alsolami, F., et al. (2021). Blockchain and PUF-based lightweight authentication protocol for wireless medical sensor networks. *IEEE Internet Of Things Journal*.

Wang, S., Qureshi, M. A., Miralles-Pechuaán, L., Huynh-The, T., Gadekallu, T. R., & Liyanage, M. (2021). Explainable AI for B5G/6G: technical aspects, use cases, and research challenges. arXiv preprint arXiv:2112.04698.

Wei, K., Li, J., Ding, M., Ma, C., Yang, H. H., Farokhi, F., et al. (2020). Federated learning with differential privacy: Algorithms and performance analysis. *IEEE Transactions On Information Forensics And Security*, *15*, 3454–3469.

White, G., Zink, A., Codecá, L., & Clarke, S. (2021). A digital twin smart city for citizen feedback. *Cities*, *110*, Article 103064.

Xu, J., Glicksberg, B. S., Su, C., Walker, P., Bian, J., & Wang, F. (2021). Federated learning for healthcare informatics. *Journal Of Healthcare Informatics Research*, *5*(1), 1–19.

Yang, Q., Liu, Y., Chen, T., & Tong, Y. (2019). Federated machine learning: Concept and applications. *ACM Transactions On Intelligent Systems And Technology*, *10*(2), 1–19.

Zaballos, A., Briones, A., Massa, A., Centelles, P., & Caballero, V. (2020). A smart campus digital twin for sustainable comfort monitoring. *Sustainability*, *12*(21), 9196.

Zhang, X. Q. (2016). The trends, promises and challenges of urbanisation in the world. *Habitat International*, *54*, 241–252.

Zhang, D.-L. (2020). Rapid urbanization and more extreme rainfall events. *Science Bulletin*, *65*(7), 516–518.

Zhang, K., Ni, J., Yang, K., Liang, X., Ren, J., & Shen, X. S. (2017). Security and privacy in smart city applications: Challenges and solutions. *IEEE Communications Magazine*, *55*(1), 122–129.

Zheng, Z., Zhou, Y., Sun, Y., Wang, Z., Liu, B., & Li, K. (2021). Applications of federated learning in smart cities: recent advances, taxonomy, and open challenges. *Connection Science*, 1–28.