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Vehicle to Everything (V2X) and Edge Computing: A Secure Federated Learning-based Lifecycle for UAV-Assisted Vehicle Network: A Survey

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Abstract The Internet of Vehicles (IoV) integration and edge computing are a revolutionary change in the communication system of a smart city today. This survey paper analyzes the Unmanned Aerial Vehicle (UAV)-assisted vehicle networks as one of the ways of competing with the increasing complexity of the connected vehicle systems. The suggested framework after detailed survey improves efficiency, security, and scalability by including Vehicle-to-Everything (V2X) communication, edge computing, and UAV deployment. Federated Learning (FL) creates a privacy-preserving lifecycle of V2X networks using UAVs. UAVs serve as edge computing nodes, which increase network coverage, attain real-time data collection, and real-time processing and decision-making. FL provides the opportunity to train the vehicle-UAV model in a collaborative manner and guarantee data security. The lifecycle of the system includes data acquisition, the development of the FL-based model, and secure communication in the time of system adjustments. The proposed key points are discovered with the exploration of issues of scalability, latency, and energy-efficiency. Based on empirical findings survey, UAV-based V2X networks are useful in assisting with traffic management, automated driving, and emergency response, thus providing safer and efficient transportation systems.

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1 Introduction

Recent development of intelligent transportation systems (ITS) has placed connected and autonomous vehicles (CAVs) as the new norm, due to the mandatorily of immediate decision-making and constant communication that ensures safety, operating performance, and sustainability. ITS is based on Vehicle-to-Everything (V2X) communication which allows vehicles to send and receive data with other vehicles (V2V), infrastructure (V2I), pedestrians (V2P), and networks (V2N) [1]. The growing sophistication of vehicular networks, the growing amount of sensor data and Internet of Things (IoT) device outputs, creates important problems associated with latency, scalability, and security [2].

Combining edge computing and UAVs can provide a feasible solution to provide decentralized abilities to perform processing along with extending the network range in dynamic environments [3]. Edge computing eliminates the physical distance between data sources and computing resources, thus reducing the latency and bandwidth needs, which improves real-time decision-making systems [4]. UAV mobile edge nodes are used as flying platforms where data is collected, relayed in network, and traffic monitored in distant or inaccessible localities [5]. Another challenge faced by distributed systems, however, is significant privacy and security risk, since sensitive information collected by vehicle and UAVs is still vulnerable to unauthorized access and misuse [6]. Federated learning (FL), a machine-learning approach where players train a common model jointly, but never access raw data, offers a privacy-saving method [7]. FL allows vehicles and UAVs to be part of a global model by collaboratively learning, yet does not expose local data and instead maintains privacy and minimizes the possibility of information leakage [8]. The development of decentralized edge computing and centralized solutions has enabled a distributed computing structure where processing capability is brought closer to data sources, resulting in faster processing and less reliance on the cloud [9]. V2X functionality depends on edge enabled processing that allows instant decision making on urgent mechanisms like collision-prevention systems, traffic-management solutions, and autonomous driving. Edge enabled UAV platforms also extend this benefit by serving as mobile edge servers to form dynamic links between vehicles and infrastructure [10].

Although edge computing can be used to support time-sensitive processing, it also brings new issues in relation to the security of delicate car data, such as privacy and security. FL presents an interesting way to resolve the modern security and privacy concerns [11]. The FL framework allows distributed devices to jointly train machine-learning models and avoids transferring data that may jeopardize privacy, reducing the traffic of the communication-system. The use of FL improves UAV-assisted V2X operations wherein vehicles and UAVs are responsible to locally train standard models thereby achieving increased performance harming the privacy of the user [12]. The use of UAVs along with FL and edge computing in the V2X environment is a new research problem [13]. Effective implementation requires mechanisms of UAV mobility control, model reliability in dynamic systems and maintenance of communication integrity and aggregation capabilities [14, 15].

There are still gaps in the literature where researchers do not have standardized architectures and methodologies to facilitate the existence of the complete lifecycle that extends between the datasets acquisition and model deployment and constant updates [16, 17]. In this paper, an extensive survey and an architectural design of UAV-aided Vehicle-to-Everything (V2X) networks are provided by combining edge computing, federated learning (FL) and blockchain-based security.

The major contributions of the study are include that, Our solution is comprised of a federated-learning based lifecycle of UAV-assisted V2X network with secure end-to-end, which includes data acquisition and preprocessing steps, decentralized model training, secure aggregation, deployment, and periodic updates of the model. In contrast to the current body of literature which focuses on individual aspects, the work offers a comprehensive view of a lifecycle.

The study deals with several aims that are geared towards technical solutions and the practical demands of modern transport systems. The framework is based on the use of edge computing and UAVs to enable real-time decision-making with the assistance of low-latency processing and analytics. The system should be given immediate focus since operations, which require time, like collision avoidance, autonomous driving, and responding to emergencies, need to occur immediately. It increases network reliability and coverage by implementing mobile edge nodes made in UAVs to provide constant communication within unreachable areas, congested or disaster areas. With FL, the framework ensures the privacy and security of the data by jointly training its model with no interaction of the raw data, which addresses breaches and complies with privacy. The algorithms are designed to make UAVs and edge devices more resource effective and energy efficient and maintain their performance when the energy resources are limited. The architecture features that allow it to achieve scalability and adaptability with automatic response to changing traffic conditions, network congestion and availability of UAV systems. The framework has a diversified platform that has multiple applications, such as traffic management, autonomous driving, and novel infrastructure services.

1.1 Organization of the paper

The remainder of this research paper is organized as follows. Section II presents the related work, including the state of the Art, presented in table form. Section III discussed the detailed proposed scheme and life cycle for UAV-V2X; in this section, the proposed architecture has been discussed in detail. The characteristics and requirements for UAV-assisted wireless networks are provided in Section IV. The implementation and applications of UAV-assisted wireless networks are presented in Section V. In Section VII, applications of UAV-V2X have been covered. Section VIII discusses the challenges and state-of-the-art opportunities and solutions for UAV-assisted wireless networks. For convenience, future work and a summary of this article are presented last.

2 Related Work

2.1 Vehicle-to-Everything (V2X) and UAV-Assisted Vehicle Network

Drone-enabled technology has become widely used throughout industrial and manufacturing sectors and production facilities to boost operational efficiency in scheduling and management while providing monitoring capabilities. Centralized vehicular networks expose privacy issues due to their open architecture, leading to personal data leakage, tampering, and forgery [42].

Multiple advanced technologies, such as artificial intelligence, machine learning, deep learning, federated learning, and blockchain-enabled distributed modular architectures, have been proposed to address challenges in UAV-assisted vehicular networks with Doppler spread [43]. These solutions help reduce reliance on centralized aggregative servers, thereby maintaining system stability and ensuring crash-free operations. Unauthorized participation in these networks leads to positioning attacks that degrade system usability and create communication barriers that prevent large-scale integration of cross-domain Internet of Vehicles (IoVs). The previously published research gaps in the state-ART method are explained as follows in Table 2:

The authors [50] show that an infrastructure implementation based on Multi-Access Edge-Computing (MEC) can handle delay-sensitive applications, such as cooperative driving. The paper [51] concentrated on the formation of edge-based resource-allocation methods that were aimed at increasing the dependability of the coordination of autonomous vehicles. The authors of [52] developed an edge-computing system (based on roadside-unit (RSU)) that allows cars to offload computing-intensive processes. The importance of edge intelligence research is supported; nonetheless, edge intelligence research designs lack the ability to combine federated learning with unmanned aerial vehicle (UAV)-like mobility capabilities.

The new machine-learning technology of federated learning is useful in the field of decentralized learning in vehicles platforms that need a high level of data-ownership and privacy. The authors [53] came up with federated-learning (FL)-based traffic-prediction systems in vehicular systems that allowed distributed analysis without centralized data repository requirements. Pokhrel and Choi (2020) proposed a federated learning model based on mobility-aware dynamic vehicular network and showed that it is an effective model update framework in real-time. Author [54] came up with a hierarchical FL system which utilizes synergy between RSUs and cloud servers to train and aggregate models optimally. Most FL-based systems today only operate ground-based nodes, without any aerial support features or lifecycle coordination, such as model deployment, streamlined feedback, and secure updating in dynamic settings [55].

Security, along with the privacy requirements, is a critical factor in developing federated learning in communication systems based on UAVs. The research team [56] focused on the creation of secure aggregation principles to the federated platforms as an opposition to possible attacks. Afterward, researcher [57] gave a comprehensive evaluation of FL privacy tools, such as differential privacy, secure multiparty computation, and homomorphic encryption. Additional research [58] investigated trust-based anti-jamming schemes to achieve security of UAV communications in unfavorable conditions. These papers discuss FL, UAVs, and V2X as individual assets, but they do not come up with an overall security strategy that can capture the whole learning process.

Table 1. State of the Art Key Contributions with Challenges

Technology	Key Contributions	Challenges	References
V2X Communication	Enabled real time communication between vehicles infrastructure and pedestrians to improve road safety and traffic efficiency.	High latency in congested networks with limited scalability and coverage.	[18–20].
Edge Computing	Reduced latency by moving computation closer to data sources and end users.	Resource allocation complexity in highly dynamic environments.	[21–23].
UAV Assisted Networks	Provided aerial support for traffic monitoring emergency response and data collection.	Energy constraints limited flight time and trajectory optimization difficulty.	[9, 24, 25].
Federated Learning	Enabled privacy preserving collaborative model training by keeping data decentralized.	Communication overhead convergence instability and security vulnerabilities.	[26–28].
V2X with Edge Computing	Enhanced real time processing for autonomous driving and intelligent traffic management.	Scalability challenges in dense networks with mobility handling.	[19, 23, 29].
V2X with UAVs	Improved network coverage reliability and aerial data relaying capabilities.	Energy efficiency limitations trajectory planning and security risks.	[30–32].
Edge Computing with UAVs	Utilized UAVs as mobile edge nodes for low latency services in remote areas.	Resource allocation and energy constraints under dynamic conditions.	[33–35].
Federated Learning with Edge Computing	Supported distributed privacy preserving learning at the network edge.	Model convergence issues trust management and heterogeneous devices.	[30, 31, 36].
Federated Learning with UAVs	Enabled collaborative learning from UAV collected data with privacy protection.	Energy limitations communication overhead and synchronization complexity.	[34, 37, 38].
V2X Edge UAVs and Federated Learning	Proposed integrated architectures for secure scalable and real time vehicular networks.	Lack of unified frameworks ensuring scalability and energy efficiency.	[39–41].

Table 2. Related literature on federated learning UAV assisted vehicular networks and vehicle to everything

Title of the Research Paper	Proposed Framework	Research Gap	Limitation	Proposed FL based UAV V2X
Vehicle to Everything and Edge Computing [44]	UAV assisted edge computing for vehicular task offloading	FL architecture IoD paradigm and security categorization	Privacy exposure and communication overhead	Hash based encryption area wise segmentation
Federated Learning for Data Privacy Preservation [45]	Privacy preserving FL framework for vehicular CPS	Blockchain consensus and distributed ledger control	Model poisoning vulnerability and high computation cost	Bandwidth optimization and cross chain interoperability
Real Time Radio Map Construction [46]	Dynamic UAV assisted MEC adaptation	FL learning and IoD standardization	Limited real time attack defense	Blockchain AI integration and off chain channels
Blockchain Based Secure UAV Data Sharing [47]	Secure blockchain enabled UAV data exchange	IoD delivery and cross chaining architecture	Energy overhead and limited V2X integration	Lightweight blockchain and low latency FL design
Exploiting Federated Learning [48]	Energy efficient FL with UAV optimization	Multi UAV coordination and predictive learning	Security exposure and blockchain overhead	Cross chain integrity and permissionless access
UAV Assisted Wireless Powered MEC [49]	Energy aware UAV deployment strategy	5G connectivity and remote cloud reliance	Flight time limitation and energy adaptation	Secure segmentation and GPS coordination

2.2 Mobile Edge Computing and Internet of Vehicles using Blockchain.

Internet of Vehicles (IoV) can be considered an extension of conventional vehicular networks, which involve smart vehicles, roadside infrastructure, and cloud services to communicate data on-demand and manage traffic intelligently and allow autonomous driving. The IoV applications have become very intricate and pose a great challenge to ensure that they can process data with low latency, and it is still guaranteed that the data is secure and not subject to privacy. Mobile Edge Computing (MEC) is a crucial technology, which allows the implementation of computational resources at the edge of the network, in close vicinity to vehicles [59]. MEC implementation of the IoV networks enables the distributed computing capability by moving the processing tasks off load of the cloud servers thus reducing latency, minimizing bandwidth usage, and increasing real-time operational decision-making. The implementation of MEC-based IoV systems has brought about security and privacy issues, which specifically impact confidential automotive data [60]. The proposed solution to address these privacy issues is Federated Learning (FL), a practical, privacy-preserving machine learning approach for IoV and MEC systems [61]. FL operates differently from traditional centralized learning because it enables distributed model training directly on edge devices, including vehicles and roadside units (RSUs). The distributed training method of FL protects data privacy and minimizes network traffic, making it ideal for IoV systems [62]. FL enables vehicles to collaborate on model training without revealing raw data, thereby improving privacy protection and system performance and accuracy.

3 Methodology

The current research follows the systematic literature review approach designed using the PRISMA framework as shown in Table 3 and is clearly defined with the lifecycle architecture presented in Figure 4, which enhances the methodological consistency of conceptual modelling and evidence synthesis. The literature search was carried out in IEEE Xplore, Scopus, Web of Science, ACM Digital Library, and ScienceDirect including the works published in 2018–2025. The preliminary list of 700 articles was retrieved using controlled key-word searches in terms of UAV-assisted V2X communication, mobile edge computing, federated learning, blockchain-based security, and vehicular intelligence. After a step of duplicates removal, title and abstract screening had been done, with the exclusion of non-technical surveys, domain-divergent blockchain applications and studies that did not have system or algorithmic depth. An eligibility assessment was then done in the full-text by mapping all candidate studies to one or multiple lifecycle phases described in Figure, including blockchain-based trust establishment, data acquisition and edge preprocessing, federated model training and aggregation, edge-level optimization and scheduling, and blockchain-enabled integrity and auditability. This systematic shifting produced 107 end-result studies that directly relate to at least one aspect of a lifecycle, and as such, the architectural relevance has been guaranteed, and narrative drift has been avoided.

The analytical synthesis was conducted by use of a stage-based classification approach, which is in tandem with the suggested lifecycle architecture but not a descriptive overview of individual works. All the identified studies were methodically analyzed in terms of their architecture, mechanism of learning or optimization, security enforcement model, and analysis in terms of energy usage, latency, scalability, and mobility limitations. This can be cross staged compared across federated learning convergence behavior, UAV deployment strategies, task offloading policies, and blockchain overhead, and any gaps in integration can be revealed, which could not be detected by narrative reviews. Considering the lifecycle mapping and the comparative technical criteria as the basis of the analysis, the methodology provides a defensible design of the survey that goes beyond the level of the definitional discourse and the provision of a system-level synthesis of the existing research, which qualifies the study as a rigorous, architecture-driven review as opposed to a descriptive overview.

4 Preliminary Knowledge of UAV-assisted wireless network for V2X

In Figure 1, a common approach for UAV-assisted wireless networks is to implement an architecture that enhances wireless communication and improves data transmission and network coverage by integrating uncrewed aerial vehicles (UAVs) with terrestrial and satellite networks [63]. Network efficiency improves through UAVs that function as aerial base stations and relays, and through mobile edge computing (MEC) nodes in areas with high mobility, disaster recovery zones, and locations without traditional infrastructure [64].

A UAV-assisted wireless network architecture consists of three fundamental layers: the UAV Layer, the Edge Computing Layer, and the Core Network Layer. Here is a detailed discussion of the centralized and decentralized architectures.

4.1 Centralized Architecture

Figure 2 shows the centralized approach, in which all UAVs are connected to a centralized cloud server. UAVs receive their instructions, communication tasks, and task assignments from either a ground station (CGS) or a cloud-based network controller [65]. The central controller manages UAV deployments and optimizes network resources while preventing UAVs from interfering with each other.

UAVs create communication pathways by combining millimeter-wave (mmWave) and free-space optical (FSO) technologies with sub-6 GHz 5G/6G technologies to establish high-speed user connectivity. In the centralized architecture, the central aggregator serves as the process coordinator, combining model updates from UAVs and ground devices [66]. The system merges enhanced global model updates while returning the updated version to connected devices. The aggregator maintains both integrity and security of the federated

Table 3. PRISMA Based Study Selection Summary

PRISMA Phase	Description	Papers
Identification	Records identified through database searching	700
Screening	Records after duplicate removal and abstract screening	412
Eligibility	Full text articles assessed for lifecycle relevance	176
Included	Studies included in final qualitative synthesis	107

learning process through secure aggregation protocols and trust management systems.

4.2 Decentralized Architecture

Figure 3 shows that UAV-assisted wireless networks based on blockchain adopt a decentralized architecture that removes central controllers to achieve scalability, privacy, and distributed intelligence between UAVs and edge devices [67]. A decentralized approach enables UAVs to handle autonomous communication, local data processing, and machine learning model training through Federated Learning rather than using cloud servers or ground-based control centres [68]. The decentralized approach delivers maximum benefits to resource-limited networks and fast-changing operational environments, including vehicular networks, disaster response operations, and remote sensing applications [69].

4.3 Proposed Lifecycle UAV-V2X Adopting the Federated learning

The suggested U-V2X lifecycle is a combination of blockchain technology, unmanned aerial vehicles (UAVs), and federated learning to improve the security and efficiency of Vehicle-to-Everything (V2X) communication networks [70]. The framework considers the challenging data-management problems, privacy, and dynamic-vehicle environments with real-time decision-making requirements by supporting the secure vehicle to infrastructure to vehicle communication and vehicle to other entity communication. The lifecycle will start with gathering of data through vehicle sensors, roadside units and UAV-mounted cameras that will provide real-time traffic, environmental and hazard data [71]. Edge computing servers, placed in proximity to the sources of data, do preliminary data processing, such as filtering and aggregation, to decrease latency and bandwidth consumption [72]. Federated learning also allows training distributed models on the network to obtain a global model and maintain data privacy by sharing the information securely. The use of blockchain technology to create a tamper-evident ledger to document data transactions, model updates and access-control policies will build trust and accountability. Training on edge devices is done iteratively on proprietary datasets before the secure aggregation step is done in central server [73]. The decentralized storage plan ensures privacy of sensitive data as it does not centralize data thereby reducing the risk of privacy that comes with the traditional machine-learning methodologies.

4.3.1 Methodology Details

To enhance reproducibility and practical clarity, this section elaborates on the implementation-level methodology of the proposed UAV-assisted V2X federated learning lifecycle, including message flows, system parameters, and timing behavior across different operational stages.

In the section, we enhance the reproducibility and practical clarity by defining the implementation-level methodology of the proposed UAV-assisted V2X fed-

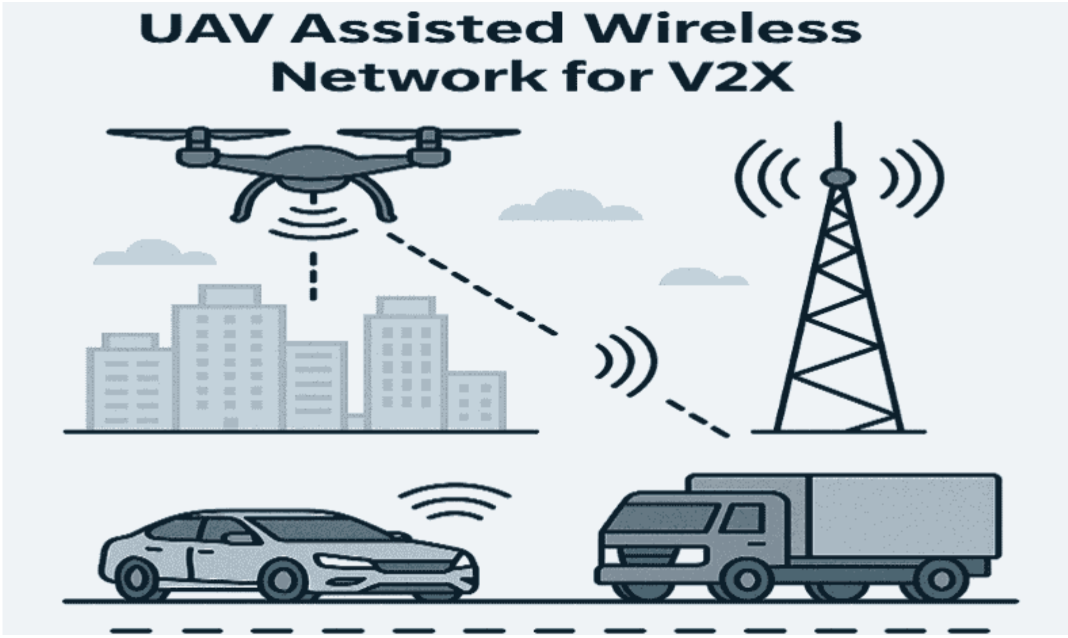

Figure 1. UAV assisted wireless network for V2X recreated by the author based on studies [4, 14, 31–43, 45–54, 66].

erated learning lifecycle, specifically, the message exchange, system roles, operational parameters, and timing dynamics in different execution phases. The methodology conceptualizes a collaborative vehicular intelligence environment whereby many system entities are connected via coordinated communication and instructional processes. The Internet-of-Vehicles (IoV) participants are also imagined as vehicular nodes, which are provided with onboard sensing devices, V2X communication interface, and local computation resources, hence allowing continuous data acquisition and training a federated learning model locally under mobility constraints. The Unmanned aerial vehicles are described as aerial edge nodes, which dynamically deliver computation offloading, intermediate storage, data aggregation and relaying services, further improving the coverage of edge intelligent in the case where terrestrial infrastructure is limited or overloaded.

Roadside units are assigned as fixed infrastructure elements, which serve vehicle-to-infrastructure communication and get involved in federated aggregation processes where they exist, thus providing a stable connection and additional computing power. The system is supported by a consortium blockchain network that does authentication of nodes, verification of trust, access control policy and permanent recording of updates to the model and system transactions hence integrity and auditability of the entire learning lifecycle. Local model updates are securely aggregated by assigned edge entities that can be placed on UAVs, roadside units, or edge servers and are tasked with the process of distributing the outcome global model to the involved nodes. The combined cooperation and to coordinate the learning process, ensures safe cooperation, and adjust the use of resources to heterogeneous elements of vehicles and aerial vehicles.

4.4 Proposed architecture for UAV - V2X lifecycle

In Figure 4, we proposed a UAV-V2X basic lifecycle architecture, divided into five stages, using federated learning. In the first stage, UAV-V2X registers the IoV node in the designed consortium chain after a proper verification and validation. During this first stage, Hyperledger Blockchain securely records the transaction and verifies and validates the enrolment request by initiating chain transactions. Blockchain executes transactions and records logs. In the second phase, a wireless sensor network (located between the first and second phases) receives IoV-enabled data collected in the distributed vehicular environment. The collected data points are then processed using the suggested UAV-V2X standardized lifecycle. The collected data will be preprocessed and

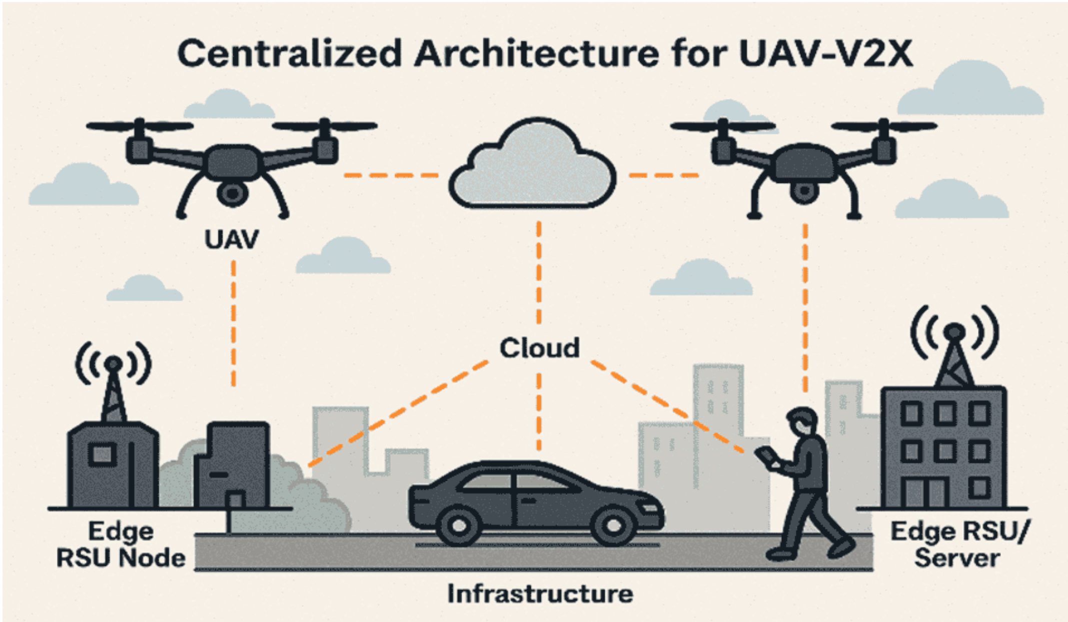

Figure 2. Centralized architecture for UAV V2X recreated by the author based on studies [4, 14, 31–43, 45–54, 66].

filtered to remove distortions, noise, and duplicates.

The second phase involves the archiving of data to be executed later and generate reports. The third step involves the input of preprocessed data to the Federated Learning Model (FLM) where the decentralized AI model is trained on the Internet-of-vehicles (IoV) nodes, keeping the raw data locally and improving privacy. The fourth stage involves a computational node that mediates between the blockchain ledger and the lifecycle and schedules the execution of transactions. Therefore, UAV-V2X performance is consistent and consumes fewer processing resources, since edge nodes do not require so much computing resources as fog, cloud or special units. Security and privacy processes are implemented on the information in the proposed UAV- V2X framework in the fifth stage. The infrastructure based on the blockchain-ledger aims to accomplish two main goals: the protection of data against malicious attacks and at the same time ensure integrity, transparency and provenance; the second, prevention of forgery and tampering and, consequently, preservation of privacy and security. At the fifth stage, federated learning coupled with blockchain is promoted to maintain the security and privacy of UAV-V2X networks. This brings in a secure local storage of data and offers integrity, with trust-based systems. The combination of these technologies provides secure, efficient, and scalable transportation systems. The future studies must focus on the development of UAV -V2X networks to eliminate energy-efficiency and scalability limitations and implement complex threat-detection solutions to enhance network security and privacy. In Figure 4, we suggest a Federated Learning -Based UAV -V2X Lifecycle Architecture. The illustration presents a five-step lifecycle including (i) consortium-blockchain-based node registration and trust creation, (ii) distributed vehicular and UAV data collection with edge preprocessing, (iii) decentralized federated model training and secure aggregation, (iv) edge level task scheduling and optimization, and (v) blockchain based integrity, auditability, and enforcement of privacy. The design puts a strong focus on the separation between data flow and control and trust channels and emphasizes on the lifecycle continuity over individual components.

5 Discussion on the characteristics and requirements for UAV-Assisted Wireless Network

In this section, we outline the characteristics and requirements for UAV-assisted wireless networks. The characteristics are first presented, followed by the requirements for UAV-assisted wireless networks.

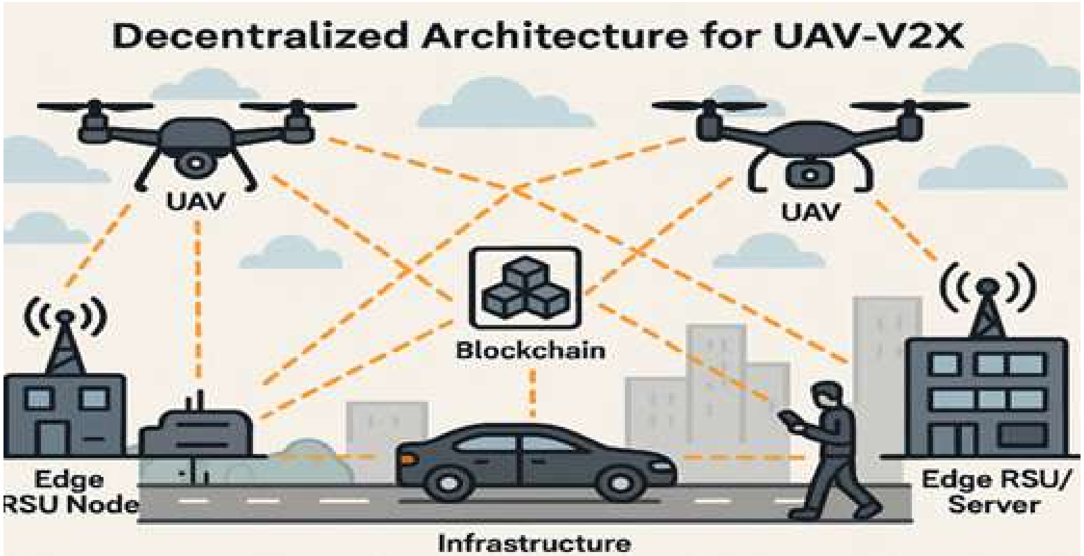

Figure 3. Decentralized architecture for UAV-V2X recreated by the author based on studies [4, 14, 31–43, 45–54, 66].

5.1 Characteristics for UAV-Assisted Wireless Network

UAV-assisted wireless networks enable the sensing and identification of physical entities in the air. Leveraging the flexibility and versatility of UAVs, these networks exhibit several unique characteristics.

1. The following features are to be used in UAV-Assisted Wireless Network: Wireless networks with the help of UAVs help in sensing and detecting physical objects in the air. Due to the flexibility and versatility of UAV, these networks possess a number of unique characteristics. a. Heterogeneous Devices: Existing networks are very heterogeneous as they comprise of different physical devices that are linked through platforms that are managed by various vendors and technologies. This heterogeneity may hinder a device communication in UAV-assisted networks [74].
2. Line-of-Sight (LoS) Communication: UAVs are on higher altitudes, and thus they stand more chances of LoS interaction with the land users and other network nodes, which minimizes signal blockage and improves the quality of communication as compared to terrestrial networks [75].
3. Rapid Deployment: UAVs offer a rapid-deployment platform in regions with either no, or damaged or overloaded, conventional infrastructure like in disaster zones or isolated locations. They are appropriate to respond in the case of an emergency and temporary network development [76].
4. Connectivity with Existing Networks: UAVs cooperate with land-based and satellite networks to provide continuous connectivity, which acts as a bridge in providing aerial communication, backhaul, and edge computing solutions to form heterogeneous network spaces [77].
5. Openness and Flexibility: Interfaces and applications are open resources that can allow developers to expand UAV-assisted networks. UAV flexibility allows the applications to be customized and scaling the network to improve the service performance of the UAV [78].
6. Wide Coverage and Continuous Connectivity: The FANETs may be formed cooperatively by a swarm of UAVs that maintain constant communication with terrestrial equipment. UAVs' adaptability in the air provides a practical and efficient way to expand the communication coverage of ground networks. Furthermore, continuous communication between UAVs and ground equipment may be developed to ensure real-time data exchange, given reliable LoS links [59, 79]. To maximize the UAV deployment plan, an energy-efficient information coverage issue was created in [60]. Heterogeneous UAV deployment was examined

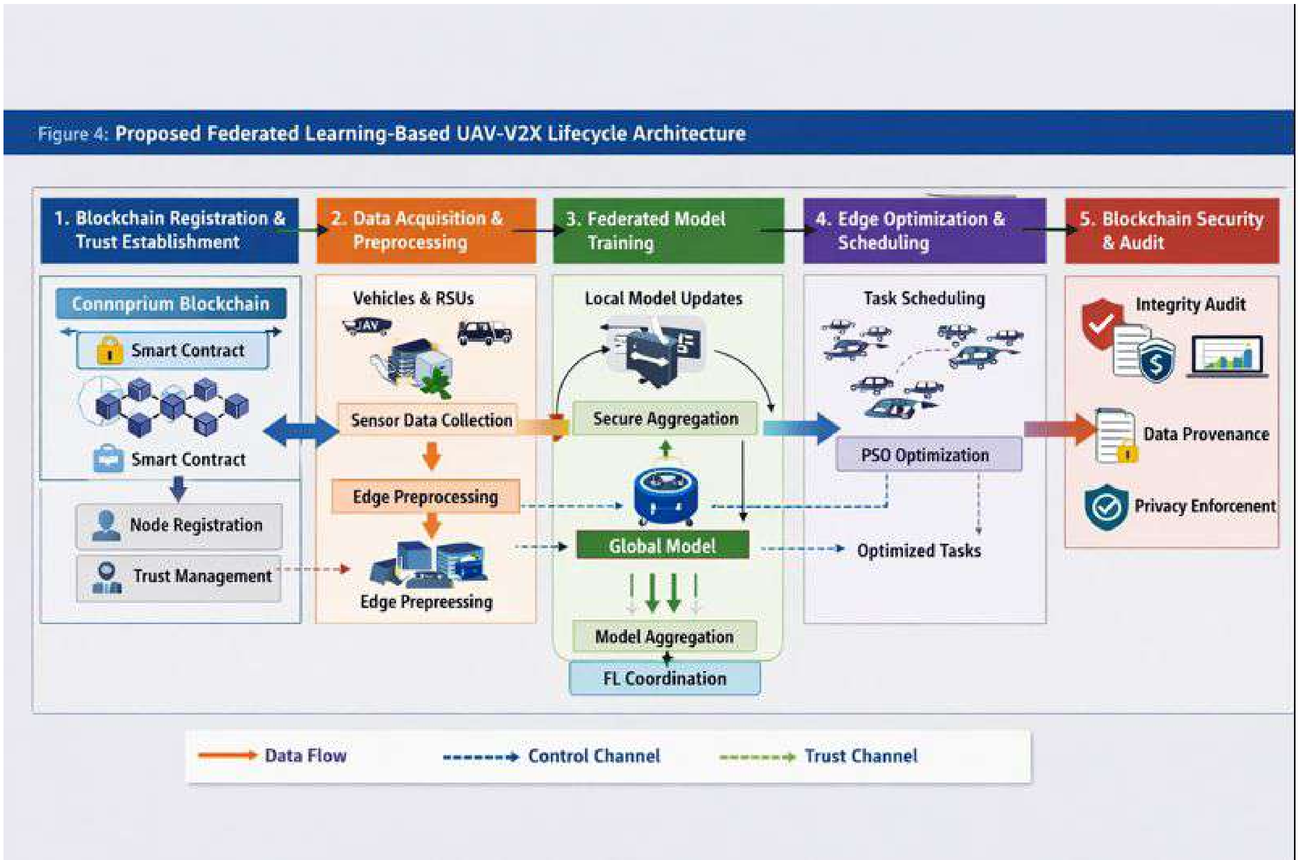

Figure 4. Proposed UAV-V2X federated lifecycle.

in [61] to provide wireless coverage and reduce deployment latency in a specific geographic region.

7. Expandability and Operation: With the expandability of UAV-assisted wireless networks, many smart devices (such as robots and driverless cars) and UAVs may be combined into a single ecosystem [79]. Mobile device deployment is made easier and more convenient by the flexible operation capability. As a result, it can improve resource utilization and reduce overall deployment costs.

5.2 Requirement for UAV-V2X (UAV-Assisted) Wireless Network

The implementation of UAV-assisted wireless networks uses Unmanned Aerial Vehicles (UAVs) to expand communication coverage and capacity and improve reliability. The networks prove beneficial when standard infrastructure does not exist, has been damaged, or is inadequate in rural regions, disaster zones, and during significant public events. Several technical, operational, and regulatory requirements must be fulfilled to create and deploy an effective UAV-assisted wireless network.

To create and implement effective UAV-assisted wireless network, several technical, operation, and regulatory requirements are required. These requirements are expounded by the following subsections.

e) Communication Requirements: UAV communication should be capable of high-speed transmission of video streaming, real-time surveillance and IoT connectivity. The self-driving systems and the emergency response system demand low-latency crucial communication [63]. Connection between UAVs and ground users should have stability and reliability regardless of the operating conditions. The network design should be able to support many users and devices at once without affecting the performance significantly [80].

f) Federated Learning by using Artificial Intelligence and Machine Learning: AI algorithms are used to optimize the UAV positions and flight paths and regulate the use of resources [81]. Predictive maintenance is made possible through machine learning whereby hardware failures are predicted and therefore minimize the disruption in operations. Components of machine-learning are an essential element in the federated learning training and testing [82]. The capability of UAVs to interpret the changes in the environment and the behavior of the user improves the functionality of the networks.

g) Energy Efficiency Requirements: UAVs can utilize solar panels and other energy-harvesting devices to increase their flight duration, as well as reduce-power processors, antennas, and sensors to minimize the use of energy. The paths of flight and hovering techniques are also energy-efficient and cut down on the consumption of power [83].

h) Security and Privacy Requirements: Communication between UAVs and ground users must be encrypted to prevent eavesdropping and data breaches. Only authorized UAVs and users should be allowed to access the network. UAVs must be equipped with anti-jamming and anti-spoofing mechanisms to ensure secure operation [84].

i) Network Architecture Requirements: UAVs should seamlessly integrate with existing terrestrial networks (e.g., 5G, LTE) to provide extended coverage and capacity. UAVs need robust backhaul links to connect with the core network, either via satellite, ground stations, or other UAVs [66]. In large areas, UAVs may need to relay data through multiple hops to maintain network connectivity [85].

j) LoS Links: Using LoS connectivity, UAVs can serve as airborne communication platforms to interconnect ground-based equipment. Reliable communication between UAVs and ground equipment can be enabled via LoS connectivity. Drones may fly between 500 and 2000 meters, and their height can be changed to improve communication quality [86]. Numerous works in literature have proposed the construction of LoS linkages for UAV-based communication models. A UAV-based communication system with a free-space optical backhaul link to the ground station was presented, considering a LoS connection in the radio frequency (RF) link.

k) Sensing Ability: To increase the effectiveness of the sensing service and gather data in the air, UAVs are equipped with many sensors. The development of wireless technologies has enabled real-time data transfer and a smooth connection with smart devices. By keeping an eye on the surroundings and traffic data, UAVs' sensing capabilities allow ITS and smart cities [87]. To perceive dispersed data at target locations, a vehicle-assisted multi-UAV routing and scheduling strategy was presented in different categories. To autonomously collect data for a UAV-assisted mobile crowdsensing system, the route-planning and task-assignment problem was thoroughly examined. To increase data collection effectiveness, state-of-the-art suggested an energy-efficient mobile crowdsensing system for mobile terminals' mobility and sensing [88].

5.3 Implementation for UAV - V2X Assisted Wireless Networks

The integration of UAV-based wireless networks for Vehicle-to-Everything (V2X) communication utilizes uncrewed aerial vehicles (UAVs) to optimize vehicular networks by improving connectivity and reliability and enhancing performance. The V2X communication system enables vehicles to exchange information with other vehicles (V2V), infrastructure (V2I), pedestrians (V2P), and networks (V2N). At the same time, unmanned aerial vehicles (UAVs) are essential elements that form the part of coverage expansion, latency reduction, and the ability to support dynamic network requirements in a range of operational conditions. The implementation structure begins with the discovery of the key use cases, including traffic management, emergency services, rural connectivity, autonomous vehicle support, and crowd management. The resulting system architecture is based on the use-case advice and features the UAVs as air nodes, ground vehicles with V2X communication devices, roadside units (RSUs), a backbone network to enable the provision of back-haul connectivity and a control center to coordinate the UAV courses and allocate network resources.

5.3.1 Current Status of Edge Computing and Related Implementation Issues in UAV-V2X

The merging of edge computing technologies with UAV-assisted Vehicle-to-Everything (V2X) communication is developing a new, innovative transportation system infrastructure. The real-time analytics and localized data processing aspects of edge computing suit applications with vehicular latency requirements, including cooperative awareness, obstacle detection, and autonomous driving. Modern UAV-V2X systems leverage UAVs as mobile edge nodes to fill network gaps, extend communication range, and perform intensive data processing near information sources [88–90].

Numerous implementation issues are limiting the mass application of UAV-assisted edge computing in V2X systems. The most notable of these are inherent resource limitations of UAVs, i.e., limited battery capacity, limited computational power and limited payload capacity. UAV platforms lose power quickly at high speeds, in data processing, and thus limit the time of long missions and require periodic refueling or system replacement [91]. In turn, the advancement of effective offloading mechanisms, energy-conscious addresser algorithms, and lightly computational procedures is the subject of present-day research attention. One of the key problems is mobility management and network stability. In UAV-V2X networks, both UAVs and ground vehicles move unstructured to generate very dynamic networks and frequent connectivity disruptions [92–100].

Strong mobility-conscious protocols, which are supplemented with dynamic routing schemes are necessary that will allow smooth handovers and link quality maintenance during constant network reconfigurations. Complexity in integration and interoperability, the heterogeneous devices coexist in dual ways with heterogeneous communication standards, e.g., DSRC, C-V2X, and 5G NR-V2X. Lack of standardized frameworks as well as the lack of testbeds in the real world makes a major obstacle to the verification of proposed solutions and the implementation of strict comparative experiments. Current methodologies are largely assessed by simulation or controlled experiment experiments that can be too limited to reflect all the scope of the issues of urban deployment that is faced in practice [95–98].

The developing demand proposes the formation of standardized testing systems, including optimization methods and open-source testing environments, to help to provide full evaluation of UAV-V2X solutions. The UAV-V2X edge systems used today are designed at various levels of hierarchy with the vehicles and RSUs acting as terminal nodes and connected to the central edge servers. UAVs can be described as aerial bridges or mobile edge servers, which have built-in computational units, catching capacities as well as the communication modules, which can be used to complete a real-time task of vehicle data processing [96]. The designs at the upper layer utilize cloud service integration to have centralized orchestration, and extensive analytics and aggregation of global models when implementing federated learning. Recent studies prove that the joint usage of the servers and UAVs provide better performance in the aspects of latency, throughput, and coverage in the urban and rural settings:

a) UAV - V2X Network Platform

The first stage will involve the network design by integrating the use of UAVs, which will involve defining the coverage gaps, and strategic positioning of the UAVs to reach all areas with maximum coverage and minimum interference. Trajectory-planning algorithms are used to maintain constant coverage at the minimum energy consumption. Designers develop communication protocols that allow UAVs to communicate with DSRC (Dedicated Short- Range Communications) and C-V2X standards without any issues [69, 100, 101]. The creation of UAV-to-Vehicle protocol (U2V) and UAV-to-Infrastructure (U2I) communication allows efficient data relaying of UAV, vehicles, and infrastructure [89, 97, 99]. Successful V2X communication by UAV is conditional on spectrum and resource management; frequency bands are allocated and dynamic beamforming methods are used to reduce interferences [100–105].

b) UAV - V2X Data processing Platform

UAVs have the edge computing features that allow V2X data processing on-board, hence preventing delays and improving reaction times. The cache of map data and traffic conditions also enhances performance by the UAV. The key to successful V2X communication is the integration of 5G, fast cloud connection, and advanced analytics with centralized control. The security is guaranteed by encryption, authentication procedures, and anti-jamming measures [70, 101, 102].

c) UAV - V2X Implementation Platform

Simulation tools, e.g., NS-3 and OMNeT++, are used to test performance, reliability, and scalability of a system and supported with real-life field tests. The collaboration of the major technologies, such as 5G and further, AI and machine learning, computer vision, and blockchain enhances the UAVs path, enhances security, and makes possible real-time object detection and situational awareness [103, 104]. The versatile benefits of UAV technology require the solutions to the energy limitations, interference control, regulatory conformance, and scalability, in terms of effective energy design, sophisticated interference control, regulatory compliance, and scalable architecture.

d) UAV - V2X Operational Platform

The application of UAVs in V2X setting demonstrates three example scenarios that could include urban traffic control, where UAVs are hired to detect traffic congestion and relay real-time traffic control to traffic lights and vehicles; highway safety, where UAVs extend and complement existing collision avoidance systems; and disaster management, where UAVs can create ad hoc V2X networks to coordinate emergency vehicles [105]. The major trends of UAV-assisted V2X technology in the future are anticipated to focus on swarm UAV deployment to provide larger coverage and redundancy, integration with 6G networks, and autonomous UAV development to ensure dynamic environmental adjustment [72, 100, 105]. V2X will enable the development of new transportation ecosystems as implementing UAV-assisted wireless networks will guarantee increased safety, efficiency, and reliability.

5.3.2 Application for UAV - V2X - Assisted Wireless Networks

The versatile nature of the UAV-assisted Vehicle-to-Everything (V2X) wireless network is based on the unique potential of uncrewed aerial vehicles (UAVs) to provide a greater level of connectivity and contribute to the improvement of safety and efficiency in the transportation system. These applications can work in both urban and rural and emergency conditions since conventional ground-based networks have difficulties in addressing such issues. The primary uses of UAV-V2X-assisted wireless network are:

e) Traffic Management and Optimization: UAVs will be able to fly above the congested routes and track the traffic flow and gather real-time information, which will be transmitted to vehicles and traffic management centers. UAVs have the capability of stopping traffic jams to get a view of the traffic and record real-time information, which is transmitted to vehicles and the traffic control centers. UAVs can scan the accidents, roadblocks or dangerous situation fast and signal other vehicles and authorities that are nearby to take the necessary measures [106].

f) Emergency Services and Disaster Response: UAVs have real-time connectivity and live video transmission, directing rescue forces to the location of accidents in crashes. UAVs form temporary V2X networks to assist emergency rescue missions, provision delivery, and network connectivity in case of natural disasters like earthquakes and floods [73]. UAVs assist rescue personnel to track individuals and vehicles that are caught in remote areas that are difficult to reach, hence accelerating the rescue process [107].

g) Autonomous and Connected Vehicles: UAVs can be used in conjunction with autonomous vehicles to increase the perception of the environment by observing and providing real-time information, which promotes safety during navigation. UAVs scan up-to-date map information, which is sent to autonomous vehicles to ensure precise information regarding the road condition and road hazards. The UAV allows autonomous cars to communicate with extremely low latency, which makes them collaborate during driving and prevent collisions [100].

h) Smart Cities and Infrastructure: The vehicles can be guided to available parking spots in real-time through Smart Cities and Infrastructure, as the UAVs, parking infrastructure, and vehicles are in contact with each other. Uncrewed aerial vehicles inspect roads, bridges, and other infrastructure and transmit the gathered information to vehicles and maintenance teams, making sure that the roads and bridges are safe and efficient

[74, 100, 105]. UAVs are monitoring systems to streamline buses, trams, and the other systems of a transporting system and enhance efficiency and minimize delays [102].

i) Military and Defense Applications: UAVs may be used to offer real-time surveillance and communication to military convoys, adding to their safety and coordination. UAVs can develop safe and trustworthy V2X networks within the battlefield conditions where military vehicles can operate with command centers via communications. UAVs may also be used to collect intelligence and communicate the information to army vehicles to enhance situational awareness and decision-making [103].

j) Logistics and Fleet Management: UAV may help manage the delivery of cars, route optimization, and deliveries to be timely in urban regions. UAVs can be used to track and monitor fleet vehicles in real-time and enhance better management through real-time monitoring and hence minimize operation costs [75, 100]. UAVs may be used together with ground vehicles to deliver packages to hard-to-access regions, which improves the logistics networks efficiency.

5.3.3 Challenges and Opportunities for UAV - V2X - Assisted Wireless Networks

a) Challenges

The introduction of UAV-aided Vehicle-to-Everything (V2X) wireless networks is a disruptive solution to improve transportation systems as it provides unprecedented safety, efficiency, and connectivity. To make the most use of UAV-supported V2X wireless networks, several significant challenges need to be resolved. The most significant challenge is energy limitations because UAVs are normally powered by batteries, which have short flight times and working time. Increasing the UAV mission time, as well as assuring the quality of their functioning, requires the improvement of power-efficient communication schemes and flight-path planning [100]. Spectrum and interference management is a challenge to UAVs and ground vehicles considering that they occupy the few spectrum resources leading to congestion and interference. Beamforming, frequency reuse, and dynamic spectrum sharing methods should be adopted to mitigate the interference and allow systems to communicate with each other easily [102].

The implementation of UAV-assisted Vehicle-to-Everyone (V2X) wireless networks by constraints of both hardware and algorithms in a systemic manner obstructs the deployment of these systems to achieve reliable and scalable performance. The hardware limits on energy are one of the major bottlenecks because UAV platforms are limited by strict battery requirements that directly affect flight endurance, coverage, and processing capacity on board. As a result, energy-conscious transmission control, sparse learning, and trajectory control are needed to balance the sensing, processing and communication needs. Onboard computing is further constrained by barriers on real-time learning and optimization at aerial and vehicular nodes due to varied processing capabilities and thermal restrictions of implementing complex models. Based on this, adaptive model compression, and hardware-aware allocation of workloads will become essential. In highly mobile environments, federated learning convergence is an algorithmic problem, related to non-independent data distributions, non-persistent connections, and client loss related to UAV mobility and energy exhaustion. Unless an aggressive aggregation protocols and training strategies that are participation-conscious are used, these factors can undermine the stability of models and slow down the convergence rate.

The spectrum allocation algorithms face dynamic interference, limited bandwidth and overlapping air down channels. To maintain reliable links during varying network conditions, it is important to have efficient spectrum reuse, adaptive beamforming and the use of interference-aware scheduling. Mobility consciousness scheduling is also an important issue, because the high rates of topological variations, the variability in link quality, and unpredictable node attendance require real-time scheduling solutions, which can concurrently examine the mobility dynamics, task deadlines, and power status to prevent service interruptions. To overcome these obstacles, it requires hardware-aware, system designs that are both energy efficient and learning, as well as promote reliability of communication and security enforcement throughout the V2X lifecycle of UAV-assisted V2X.

UAV operations are completely hindered by the fact that their operations have to follow strict aviation rules which restrict the altitude of operations, create no fly zones and limit the flight duration. UAVs contribute to privacy issues by collecting information in people locations, and therefore, they need strong legal systems that can allocate the rights of the individuals. V2X networks that use UAVs are vulnerable to security and privacy threats because of their vulnerability to cyber-attacks, such as jamming, unauthorized access, and spoofing. Both encryption and authentication systems are needed when protecting sensitive data during the network transmissions to provide privacy [100–103]. The coordination of operations of numerous UAVs and vehicles is a serious problem as it is difficult to process them in the computer due to excessive computational complexity. The complexity arising with the merging of the UAV-assisted V2X networks with the existing terrestrial and cellular networks is further complicated because they must be able to operate seamlessly creating a network interoperability and manage the resources effectively [77–80]. UAVs and infrastructure associated with them are expensive to utilize and the cost is amplified when they are applied at large scale. The use of UAVs in extreme conditions and routine maintenance increases the cost of operation [102]. Despite several challenges to implementation, the benefits of UAV-assisted V2X networks are many. UAV-V2X networks are going to achieve their potential once technological improvements, regulatory facilitation, and creative solutions are pooled together to overcome the prevailing challenges. Such a development will create more innovative, safe and sustainable transportation systems [100].

b) Opportunities

Vehicle-to-Everything (V2X) wireless networks with the help of UAVs provide an opportunity to change the transportation system and address the necessary issues and create new applications. The biggest benefit of the UAV-assisted Vehicle-to-Everything (V2X) wireless networks is the enhanced connectivity which helps to cover regions that lack conventional infrastructure. UAVs extend the V2X wireless networks to locations that lack traditional infrastructure and thereby allow safer and more efficient transportation as well as bridging the digital divide. UAVs are mobile communication platforms, which form instant communication networks to ensure constant communication in case of emergency and power outages[104]. V2X networks based on the use of UAVs are beneficial in emergencies and disaster response operations. UAVs allow the swift distribution of communication systems to the disaster areas where they offer the rescue forces with real-time video feeds and data gathering [78]. The level of emergency response of UAVs allows it cooperate with first responders and relief teams, which leads to lifesaving and minimized effects of disasters. UAVs are beneficial to smart cities since they are used to regulate traffic, inspect infrastructure, and optimize public transport to decrease congestion, emissions, and costs of operation. UAVs are beneficial to novel parking systems that guide vehicles to available parking spaces, improving efficiency of transportation in the city.

The use of V2X networks based on UAVs is continually growing with technological progress. The combination of 5G and beyond technologies with AI and machine learning systems can help to optimize UAV trajectories and allocate resources and network performance in real-time. Edge computing is also a feature installed on UAVs, which allows local data processing and minimizes the latency of data flow and minimizes the amount of bandwidth needed [80, 81, 100, 104, 105, 107]. The innovations make the UAVs provide real-time surveillance, safe communication, and convoy protection in military and defense use.

5.3.4 Future direction

Progress in UAV integration, along with federated learning (FL), edge computing, and V2X communication, has occurred, while multiple open research challenges have emerged for future work. The research focuses on developing an adaptive federated learning model for dynamic mobile systems in which UAVs and vehicles operate. The conventional FL system relies on stable, continuous client connectivity and participation, but these conditions cannot be ensured in UAV-based V2X networks. The next step in research should focus on developing FL algorithms that adapt to intermittent communication and variable client availability, as well as non-IID data distributions arising from vehicular and aerial mobility patterns.

UAV energy conservation research in the future must aim at developing effective FL systems of such devices. The use of UAVs is relying on scarce battery resources because of stringent energy requirements, thus causing power failure when they are constantly involved in data gathering, calculation, and communication work. Further research is required to define the best approaches to the transfers between UAVs, vehicles, and ground infrastructure to make UAVs implement federated learning effectively and have enough time to operate. The area of research should be focused on lightweight machine learning software design, compression protocols renewal, and scheduling logic that on the one hand will be able to decide on the participation of UAVs, depending on a combination of the state of electrical power and usefulness of the communication network.

Another necessary direction of research which can be implemented in UAV-V2X networks is 6G techniques. The features of ultra-low latency, high bandwidth, and AI-native architecture of 6G systems can provide significant enhancements to federated learning and edge intelligence capacity. The future studies must examine the development of intelligent reflecting surfaces, terahertz communication, and semantic communication systems to enhance real-time, secure, and scalable federated learning activities in vehicular platforms with the help of uncrewed aerial vehicles.

Along with trust management, security is a key barrier to federated UAV-V2X systems. The privacy-saving methods proposed such as differential privacy and secure aggregation need some modifications to suit aerial-ground cooperative systems. The further work should examine powerful consensus mechanisms and blockchain ID systems, which would ensure decentralized accountability and systematic audit functions, as well as be immune to Byrne or poisoning attacks in adversarial conditions. The security of collaborative learning needs to be protected by trust models that examine activities of entities, such as vehicles, UAVs, and RSUs. To establish a paradigm of lifelong learning on a continual basis is a requirement in federated environments.

The contemporary transportation ecosystem is dynamic and stagnant predictive models become obsolete after a short period of time. FL research must also come up with structures that can facilitate the transfer of knowledge by updating them regularly and not necessarily retraining them. The system must have knowledge extraction techniques, meta-learning and continuous learning features, which perform effectively in the decentralized UAV-assisted V2X systems.

Autonomous systems gain new capabilities through UAV-vehicle teamwork, along with their ability to learn and coordinate information. Researchers developing real-time learning and reasoning systems for intelligent agents can examine decentralized decision-making approaches and swarm intelligence strategies by analyzing UAVs and other vehicles as intelligent agents. These approaches enable joint optimization, collective network resource management, communication coordination, and task assignment through cooperative perception.

Standardized simulation platforms and real-world testbeds need to be developed to integrate all elements of FL, UAVs, V2X, and edge computing into a unified setting. Current evaluation techniques remain isolated from one another because their visibility is comparatively limited. A combination of open-source, scalable simulation spaces and demonstration systems deployed across connected highways and smart cities enables developers to validate their algorithmic decisions before implementing them at scale.

6 Conclusion

The survey explored a safe FL-based lifecycle of UAV-assisted vehicle network with several fundamental phases. The first phase is data collection which allows vehicles, including UAVs, to obtain data about their surroundings, including the road conditions, road hazards, and environmental conditions. The observed data is computed locally with the help of edge computing to reduce the latency and avoid the necessity to transmit the central data. Federated learning enables several vehicles and UAVs to learn together and preserve the confidentiality and privacy of raw data. This is because the central server or edge node is provided with some aggregated and updated models by the participants and then the better model is disseminated by the central server to all the participants. The lifecycle design helps the network to tap into collective intelligence as well as safeguard privacy and security.

Inclusion of UAVs into this platform gives longer coverage, real time data relay and the ability to support dynamic network topology. UAVs are used as mobile edge computing nodes to enhance the operation of networks in highly mobile settings and the fluctuating connectivity requirements. According to the survey, some of the opportunities and limitations include the UAV energy constraint and the spectrum control measures, and the necessity to build effective cybersecurity protection measures. The research gives solutions through advanced techniques, such as energy efficient trajectory planning, dynamic spectrum sharing and encryption protocols to secure data and communication. V2X communication system and edge computing systems along with federated learning in UAV-assisted automotive networks make it possible to create more intelligent, advanced, and secure transportation systems.

The suggested lifecycle will take advantage of technology capabilities to allow real-time decision-making and protect privacy and increase scalability, which means introducing innovative and secure mobility solutions to autonomous vehicles and smart cities. The survey offers a safe FL-based lifecycle of UAV-assisted vehicle networks with several fundamental phases. The first phase of data collection allows vehicles, including UAVs, to obtain data about their surroundings, including the road conditions, road hazards, and environmental conditions. The observed data is computed locally with the help of edge computing to reduce the latency and avoid the necessity to transmit the central data. Federated learning enables several vehicles and UAVs to learn together and preserve the confidentiality and privacy of raw data. This is because the central server or edge node is provided with some aggregated and updated models by the participants and then the better model is disseminated by the central server to all the participants.

The lifecycle design helps the network to tap into collective intelligence as well as safeguard privacy and security. Inclusion of UAVs into this platform gives longer coverage, real time data relay and the ability to support dynamic network topology. UAVs are used as mobile edge computing nodes to enhance the operation of networks in highly mobile settings and the fluctuating connectivity requirements. According to the survey, some of the opportunities and limitations include the UAV energy constraint and the spectrum control measures, and the necessity to build effective cybersecurity protection measures.

The research gives solutions through advanced techniques, such as energy efficient trajectory planning, dynamic spectrum sharing and encryption protocols to secure data and communication. V2X communication system and edge computing systems along with federated learning in UAV-assisted automotive networks make it possible to create more intelligent, advanced, and secure transportation systems. The suggested lifecycle will take advantage of technology capabilities to allow real-time decision-making and protect privacy and increase scalability, which means introducing innovative and secure mobility solutions to autonomous vehicles and smart cities.

Authors' Contributions

Shafique Ahmad Awan: Conceptualization and Supervision. **Muhammad Asad Abasi**: Data curation. **Asadullah Burdi**: Visualization, Investigation. **Ali Orangzeb Panhwar**: Software. **Anwar Ali Sathio**: Methodlogy, Validation, Writing- Original draft preparation, Writing-Reviewing and Editing.

DECLARATIONS

6.1 Compliance with Ethical Standards

It is declared that all authors have complied with the ethical standards of scholarly publication. The study did not involve human participants, animal subjects, or sensitive personal data. Therefore, formal ethical approval was not required. Furthermore, it is confirmed that all authors have read and approved the final version of the manuscript.

6.2 Conflict of 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.

6.3 Funding Information

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6.4 Data Availability Information

No new data were created or analyzed in this study. Data sharing is not applicable to this article as it is based on a survey of existing literature.

6.5 Informed Consent

The study did not involve human participants or identifiable personal data. Therefore, informed consent was not applicable.

6.6 AI Assistance Disclosure

The authors declare that artificial intelligence tools were used solely for language editing, formatting consistency, and language clarity improvements only. No artificial intelligence tool was used for the generation of research data, analysis, results, interpretations, or cited scholarly content.

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