Federated Learning for Autonomous Vehicles: A Survey on Collaborative Frameworks and Reinforcement Learning Approaches

www.surveyx.cn

Abstract

This survey explores the transformative role of federated learning (FL) and reinforcement learning (RL) in the advancement of autonomous vehicle systems, emphasizing their potential to enhance intelligent transportation systems (ITS). By adopting a decentralized approach, FL facilitates collaborative model training across autonomous vehicles, addressing significant challenges related to data privacy and communication efficiency without necessitating the exchange of raw data. This approach not only preserves privacy but also optimizes resource management, thereby enhancing decision-making processes. The integration of RL within FL frameworks further augments the adaptability and responsiveness of autonomous vehicles in dynamic environments, improving control strategies and decision-making in complex driving scenarios. Despite these advancements, challenges such as data heterogeneity, model staleness, and scalability persist, necessitating innovative solutions for robust and efficient FL implementations in vehicular networks. The survey highlights ongoing research efforts to address these challenges and explores future directions for enhancing the synergy between FL and RL. By advancing these technologies, the survey underscores the potential to create more efficient, reliable, and safer autonomous driving solutions, ultimately contributing to the performance and safety of ITS.

1 Introduction

1.1 Significance in Intelligent Transportation Systems

Federated learning (FL) and reinforcement learning (RL) play crucial roles in the advancement of intelligent transportation systems (ITS), particularly for autonomous vehicles. FL's decentralized approach addresses privacy and bandwidth constraints inherent in centralized machine learning architectures, thereby enhancing decision-making and resource management. By facilitating collaborative model training without exchanging raw data, FL enables shared learning across multiple entities while safeguarding data privacy, which is vital for the optimal performance of autonomous vehicles [1].

The decentralized nature of FL effectively mitigates challenges such as high response latency and low decision-making accuracy in vehicular networks, leading to improved efficiency and safety in autonomous driving systems [2]. By addressing privacy and locality issues, FL enhances decision-making processes essential for the development of ITS [3]. Furthermore, FL aids connected autonomous vehicles in maintaining privacy and reducing communication costs, which is critical for human-like perception in open driving scenarios [4].

Integrating RL with FL further enhances ITS by optimizing decision-making in complex environments. RL improves control mechanisms for connected and automated vehicles, especially at unsignalized intersections, thereby boosting traffic efficiency and safety. This integration highlights the necessity

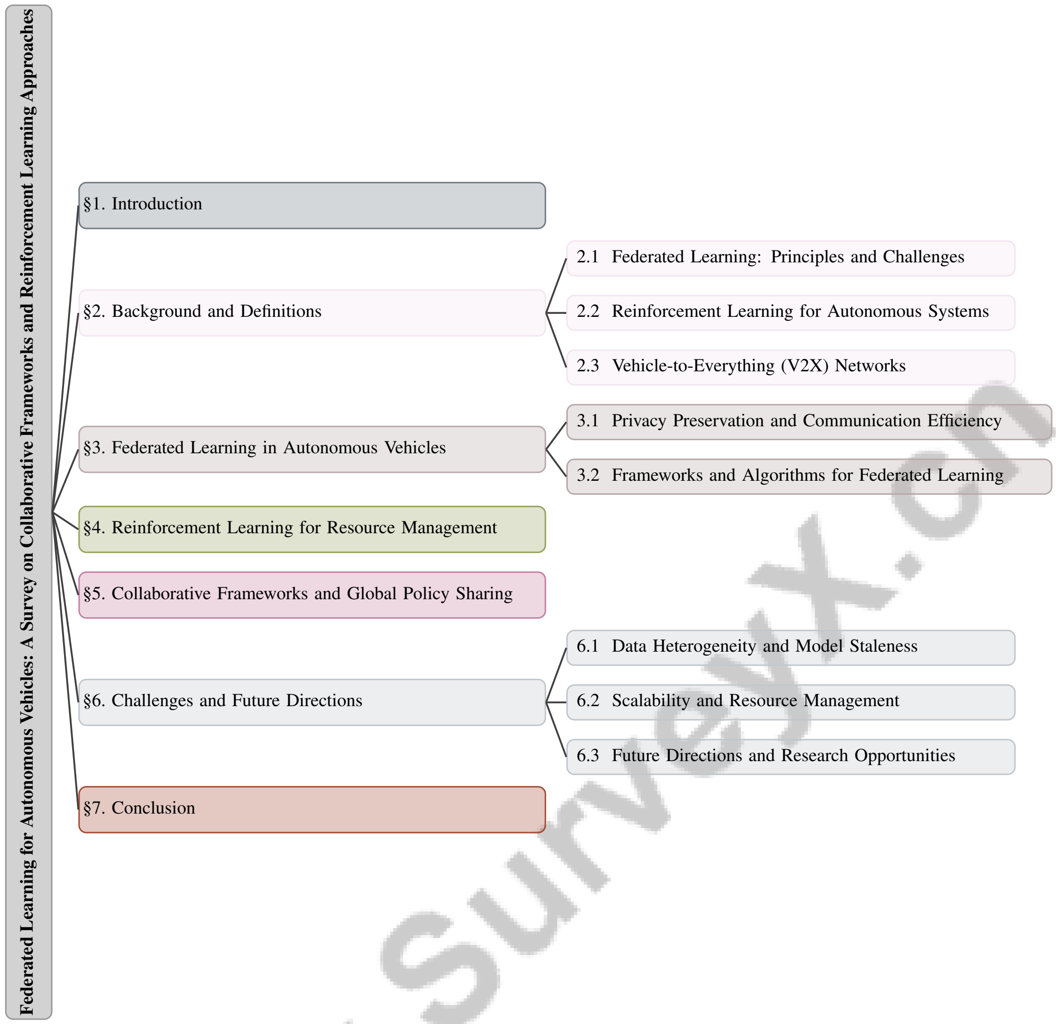


Figure 1: chapter structure

of knowledge sharing among vehicles to enhance training and performance, particularly in diverse driving scenarios.

Moreover, the hesitance of data owners to engage in FL due to resource consumption and privacy concerns underscores the need for incentivizing mechanisms within ITS [5]. By enabling model training on decentralized data, FL not only preserves privacy but also tackles locality challenges, thereby refining the overall decision-making framework within ITS [6].

1.2 Structure of the Survey

This survey is structured to navigate the complex landscape of federated learning and reinforcement learning in the context of autonomous vehicles. It begins with an introduction that underscores the significance of federated learning in enhancing decision-making and resource management within ITS, particularly in addressing dynamic vehicle behavior, privacy risks associated with mobile communications, and the need for scalable solutions adaptable to modern vehicular networks [7, 8, 9, 10, 2]. The importance of federated learning and reinforcement learning in ITS is then discussed, laying the foundation for these technologies.

The survey progresses to a comprehensive background section that defines and explains key concepts, including federated learning, reinforcement learning, collaborative frameworks, global policy sharing, V2X networks, and autonomous vehicles, equipping readers with a solid understanding of the underlying technologies and their interconnections.

AI-generated, for reference only.

Subsequent sections explore specific applications and challenges of federated learning in autonomous vehicles, addressing privacy preservation, communication efficiency, and the various frameworks and algorithms utilized. The integration of reinforcement learning for resource management is examined, demonstrating how these algorithms can optimize decision-making and enhance the efficiency of autonomous driving systems.

An in-depth analysis of collaborative frameworks that promote global policy sharing among autonomous vehicles is provided, highlighting mechanisms for exchanging learned policies across Vehicle-to-Everything (V2X) networks. This investigation reveals how such mechanisms can improve system performance and safety, particularly through federated learning approaches that enable vehicles to share knowledge while preserving privacy. The impact of contextual client selection on communication efficiency and model accuracy is also discussed, alongside the implications of real-time data exchange for optimizing traffic flow and minimizing environmental impact, underscoring the importance of adaptive learning strategies in autonomous vehicle systems [8, 11, 10, 12]. The role of blockchain technology in decentralized federated learning is also examined, particularly regarding its potential to enhance trust mechanisms.

The paper concludes with an analysis of current challenges and future directions for implementing federated learning and reinforcement learning in autonomous vehicles. This discussion encompasses critical challenges such as data heterogeneity, model staleness, scalability, and resource management. Innovative solutions like model-heterogeneous federated learning, which accommodates clients with varying computational capabilities, and Aergia, which optimizes training through task offloading, are highlighted. Furthermore, the discourse identifies significant research opportunities aimed at improving the efficiency and effectiveness of federated learning systems in diverse and resource-constrained environments [13, 14, 15, 16]. The conclusion synthesizes the key findings and emphasizes the potential of federated learning and reinforcement learning to advance autonomous vehicle systems.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Federated Learning: Principles and Challenges

Federated Learning (FL) is a decentralized paradigm that facilitates collaborative model training across multiple devices while maintaining data privacy by keeping data local [17]. This is especially advantageous in autonomous vehicles (AVs), where privacy and communication efficiency are critical. In FL, local models are trained on individual vehicles, and their updates are aggregated to form a global model, enabling shared learning without compromising sensitive information.

Implementing FL in AVs faces challenges due to heterogeneous data distribution among vehicles. Non-independent and identically distributed (non-IID) data can introduce noise, causing model drift and suboptimal performance, complicating the learning process [18]. The dynamic nature of vehicular environments further complicates communication and timely model updates [19]. Asynchronous client updates, due to varying computation speeds and data quality, hinder convergence and introduce inefficiencies, with the straggler problem posing a significant challenge in synchronous methods [20].

Incentivizing FL participation is crucial, as data owners may hesitate due to resource and privacy concerns [21]. Effective incentive mechanisms are necessary to encourage broader participation and ensure robust model training. Addressing these challenges requires innovative strategies for optimizing client selection and resource allocation while adapting to individual user data distributions [22].

Advancing FL in AVs necessitates developing adaptive architectures that balance local training and global aggregation, minimizing global loss while adhering to constraints on delay and energy consumption [19]. This involves addressing FL's optimization problem without significant computational overhead, essential for enhancing prediction accuracy and convergence speed [23].

2.2 Reinforcement Learning for Autonomous Systems

Reinforcement Learning (RL) is pivotal in advancing autonomous systems, providing a framework for learning optimal policies through interactions with dynamic environments. In autonomous vehicles (AVs), RL refines decision-making and optimizes control strategies in complex scenarios. Integrating

RL with Federated Learning (FL) enhances AV decision-making capabilities while safeguarding data privacy and minimizing communication overhead [24].

RL's effectiveness in autonomous systems is underscored by its real-time adaptability, allowing vehicles to improve performance by learning from historical and real-time data. This adaptability is crucial in navigating unsignalized intersections, optimizing traffic flow and safety [25]. The Federated Measurement and Learning System (FMLS) exemplifies this by enabling AVs to share measurement data in real-time through vehicle-to-vehicle (V2V) communication, participating in a federated learning scheme that enhances collective learning [12].

The hybrid federated and centralized learning (HFCL) approach illustrates RL's potential by allowing resource-capable clients to engage in FL while others contribute datasets to a centralized server [25]. This model ensures all vehicles, regardless of resource capabilities, can contribute to and benefit from the learning process, enhancing system efficiency and robustness.

Integrating RL with FL also addresses model and statistical heterogeneity, facilitating personalized learning experiences tailored to individual vehicles. The Gated Recurrent Unit (GRU)-based federated continual learning framework demonstrates RL's potential in predicting future data sequences and detecting illegitimate vehicle behavior, enhancing safety and reliability [26].

Reinforcement learning is crucial for developing autonomous systems, offering adaptive and efficient decision-making frameworks that enhance intelligence and autonomy. When integrated with decentralized technologies like FL and distributed ledgers, RL addresses privacy concerns and improves real-time collaboration among connected devices [27, 28]. This integration enhances learning by leveraging shared experiences across vehicles while maintaining privacy and communication efficiency, contributing to more intelligent and reliable autonomous vehicle systems.

2.3 Vehicle-to-Everything (V2X) Networks

Vehicle-to-Everything (V2X) networks are crucial for efficient communication and collaboration among autonomous vehicles, forming the foundational infrastructure for intelligent transportation systems. These networks facilitate real-time data exchange and predictive analytics, enhancing traffic management, reducing congestion, and optimizing transportation costs. Integrating technologies like federated learning and vehicular edge intelligence, V2X networks support autonomous driving algorithms while ensuring data privacy and minimizing communication overhead, contributing to smarter, more sustainable urban mobility solutions [8, 12, 10]. V2X encompasses various communication modalities, including vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-network (V2N), and vehicle-to-pedestrian (V2P) interactions, collectively enhancing situational awareness and cooperative capabilities.

Integrating V2X networks into autonomous vehicle systems significantly augments cooperative perception, enabling vehicles to share real-time data about their surroundings. This data sharing is crucial for tasks such as map management and maneuvering, as demonstrated by the intelligent networked vehicle system (INVS), which enhances these functions through V2X communication [29]. V2X-enabled cooperative perception extends sensory range beyond the line of sight, improving decision-making and safety.

Moreover, V2X networks optimize communication efficiency and model performance in federated learning frameworks. The contextual client selection pipeline, utilizing V2X messages, exemplifies this by selecting clients for model updates based on contextual information, enhancing communication efficiency and model accuracy [10]. This selective approach ensures only relevant data is exchanged, reducing communication overhead while preserving learning quality.

In addition to improving communication efficiency, V2X networks facilitate rapid dissemination of critical information, such as traffic conditions and road hazards, allowing autonomous vehicles to adapt swiftly to dynamic environments. This capability is vital for ensuring smooth and safe traffic flows, particularly in complex urban environments with high vehicle density and intricate infrastructure interactions. Integrating advanced technologies like federated learning enhances vehicle control by enabling real-time decision-making while preserving privacy, thus optimizing communication efficiency among vehicles, significantly reducing discomfort, and enhancing overall traffic safety in densely populated areas [2, 30].

In recent years, the application of federated learning in autonomous vehicles has garnered significant attention due to its potential to enhance both privacy and efficiency in data processing. This innovative approach allows vehicles to collaboratively learn from data while maintaining local data privacy, a critical consideration in today's data-driven landscape. As illustrated in Figure 2, the hierarchical structure of federated learning encompasses several key components that contribute to its efficacy. The first section of the figure emphasizes decentralized model training, efficient communication strategies, and dynamic model adjustments, all aimed at improving privacy and communication. Following this, the second section explores robust frameworks, adaptive algorithms, and essential security measures that work in tandem to advance the implementation of federated learning within autonomous vehicle networks. This comprehensive framework not only highlights the importance of each component but also underscores the collaborative nature of federated learning, making it a promising paradigm for the future of intelligent transportation systems.

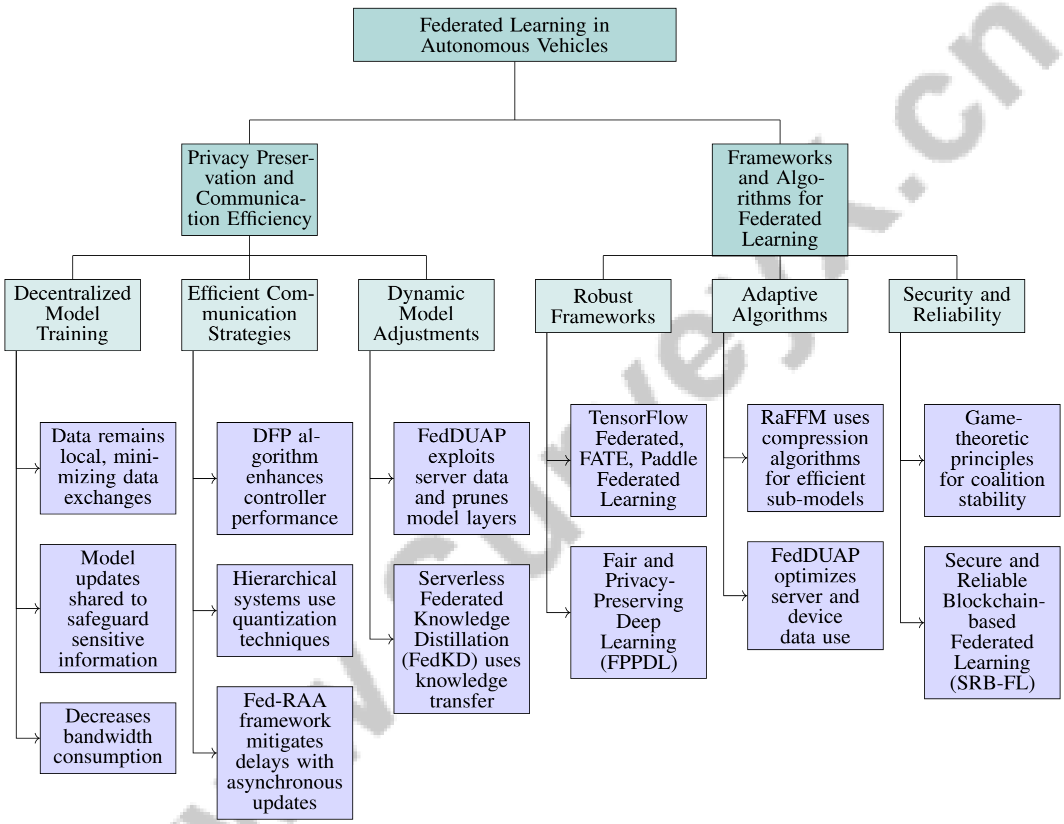


Figure 2: This figure illustrates the hierarchical structure of federated learning in autonomous vehicles, highlighting key aspects such as privacy preservation, communication efficiency, and the implementation of frameworks and algorithms. The first section focuses on decentralized model training, efficient communication strategies, and dynamic model adjustments to enhance privacy and communication. The second section delves into robust frameworks, adaptive algorithms, and security measures that collectively advance federated learning in autonomous vehicle networks.

3 Federated Learning in Autonomous Vehicles

3.1 Privacy Preservation and Communication Efficiency

Federated learning (FL) enhances privacy and communication efficiency in autonomous vehicle networks by enabling decentralized model training, where data remains local, thus minimizing extensive data exchanges [17, 23]. This ensures that only model updates are shared, safeguarding sensitive information and optimizing resource use. By reducing reliance on a central server, FL not only protects privacy but also decreases bandwidth consumption, providing a robust alternative to traditional centralized learning methods.

AI-generated, for reference only.

Method Name	Privacy Preservation	Communication Strategies	Model Adaptation
DFP[23]	Local Model Updates	Transmit Local Updates	Dynamic Federated Proximal
HLQSGD[19]	-	Quantized Model Updates	Adaptive Interval Selection
Fed-RAA[20]	-	Asynchronous Model Aggregation	Asynchronous Updates
FedDUAP[22]	Insensitive Server Data	Dynamic Server Update	Adaptive Pruning Method
FedKD[18]	Data Remains Local	Not Explicitly Mentioned	Knowledge Distillation

Table 1: Comparison of Federated Learning Methods in Terms of Privacy Preservation, Communication Strategies, and Model Adaptation. The table evaluates various federated learning algorithms, highlighting their approaches to maintaining privacy, optimizing communication, and adapting models in decentralized environments. Each method is assessed based on its unique strategies and contributions to enhancing federated learning efficiency.

Efficient communication strategies are crucial in FL. The DFP algorithm exemplifies this by allowing connected autonomous vehicles (CAVs) to learn from a broader data range, enhancing controller performance [23]. Hierarchical federated learning systems utilize quantization techniques to maintain efficient communication without compromising model performance, even under bandwidth constraints [19].

The Fed-RAA framework demonstrates the effectiveness of asynchronous updates in mitigating delays from slower clients, thereby enhancing training efficiency [20]. This approach aligns model updates more effectively, improving convergence rates and overall model performance. Furthermore, the FedDUAP method dynamically exploits server data and adaptively prunes model layers based on their importance and the non-IID nature of the data, leading to improved convergence and reduced computational costs [22].

To further enhance privacy and communication efficiency, the Serverless Federated Knowledge Distillation (FedKD) method employs Knowledge Distillation for knowledge transfer, allowing heterogeneous models to benefit from shared knowledge while accommodating unique client data distributions [18]. This approach leverages structural similarities in local datasets, optimizing network resources and enhancing performance across diverse environments.

Figure 3 illustrates the key components and strategies for enhancing privacy preservation and communication efficiency in federated learning. It categorizes the approaches into decentralized model training, communication strategies, and advanced methods, highlighting significant algorithms and frameworks cited in recent studies. Additionally, Table 1 provides a comprehensive comparison of different federated learning methods, focusing on their privacy preservation techniques, communication strategies, and model adaptation capabilities.

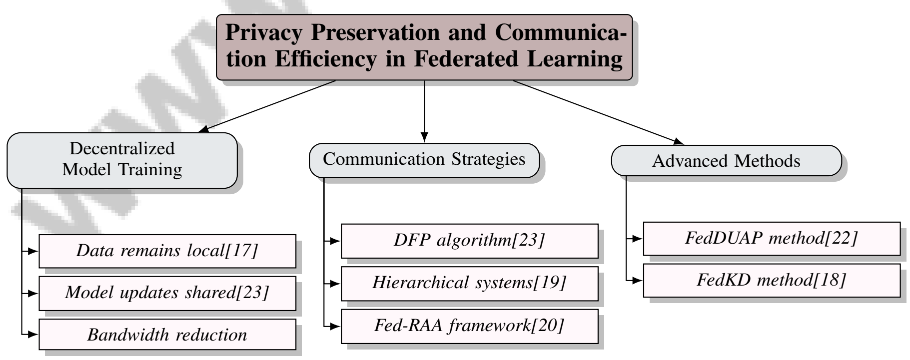


Figure 3: This figure illustrates the key components and strategies for enhancing privacy preservation and communication efficiency in federated learning. It categorizes the approaches into decentralized model training, communication strategies, and advanced methods, highlighting significant algorithms and frameworks cited in recent studies.

3.2 Frameworks and Algorithms for Federated Learning

Implementing federated learning (FL) in autonomous vehicle networks requires robust frameworks and algorithms to address the challenges of decentralized environments. Frameworks like Tensor-

Flow Federated, Federated AI Technology Enabler (FATE), and Paddle Federated Learning provide essential support for scalable and efficient model training across distributed networks [31].

The Fair and Privacy-Preserving Deep Learning (FPPDL) framework exemplifies a decentralized approach that ensures fairness in FL by evaluating local credibility and using a three-layer encryption scheme to maintain privacy [32]. This is crucial in autonomous vehicle networks, where data privacy and equitable participation are vital.

Adaptive algorithms are critical for optimizing FL processes in the dynamic environments of autonomous vehicles. RaFFM employs specialized compression algorithms and prioritizes salient parameters to create efficient sub-models, minimizing resource consumption while maintaining model efficacy [33]. By identifying impactful parameters within a foundation model, RaFFM facilitates efficient training and deployment, essential for resource-constrained vehicular networks [33].

FedDUAP integrates a dynamic server update algorithm and adaptive pruning to optimize server and device data use in training global models [22]. This method enhances convergence by dynamically exploiting available data and adaptively pruning model layers based on importance, addressing challenges posed by non-IID data distributions in autonomous vehicle networks.

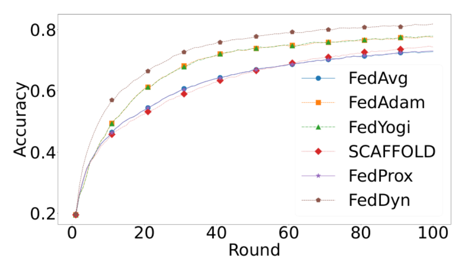
Incorporating game-theoretic principles, a proposed solution analyzes federated learning through the lens of a hedonic game, focusing on coalition stability and optimality [34]. This approach introduces an efficient algorithm for calculating optimal federating arrangements and establishes a constant-factor bound on the Price of Anarchy, ensuring stable coalition formation in FL environments [34].

Additionally, the Secure and Reliable Blockchain-based Federated Learning (SRB-FL) framework enhances the reliability of FL devices through sharding and an incentive mechanism [35]. By leveraging blockchain technology, SRB-FL ensures secure data exchanges and incentivizes participation, crucial for maintaining robust federated learning systems in autonomous vehicle networks.

These frameworks and algorithms collectively advance the implementation of federated learning in autonomous vehicles, addressing challenges such as data heterogeneity, communication efficiency, and security. By incorporating adaptive mechanisms like client-specific step size adjustments and innovative frameworks such as dynamic server updates and layer-adaptive pruning, federated learning can be seamlessly integrated into autonomous systems. This integration enhances decision-making capabilities by effectively utilizing diverse local data while preserving privacy, significantly improving overall performance metrics, including training efficiency, accuracy, and computational resource management [36, 37, 38, 22].

Method	Step *i*)	Step *ii*)	Step *iii*)	Step *iv*)	Platform
[15]		✓	✓	✓	PyTorch[3]
[16]	✓			✓	TensorFlow[4]
[17]		✓		✓	PyTorch[5]
[18]		✓		✓	PyTorch[6]
[19]		✓	✓	✓	PyTorch[7]
[20]				✓	PyTorch[8]
[21]	✓	✓		✓	Sklearn[9]
[22]		✓	✓	✓	PyTorch[10]

(a) The table compares different machine learning methods and their platforms[39]



(b) FedDyn: A federated learning framework for distributed machine learning[40]

Figure 4: Examples of Frameworks and Algorithms for Federated Learning

As shown in Figure 4, federated learning has emerged as a pivotal approach in the evolving landscape of autonomous vehicles, enhancing machine learning models while preserving data privacy. The examples provided underscore the significance of frameworks and algorithms in this domain. The first example presents a comparative analysis of various machine learning methods and their respective platforms, illustrating the diverse steps involved in the learning process and the use of popular platforms like TensorFlow and PyTorch. The second example delves into the FedDyn framework, showcasing a performance comparison of several federated learning algorithms, including FedAvg, FedAdam, FedYogi, SCAFFOLD, FedProx, and FedDyn, across multiple rounds. Notably, FedDyn demonstrates superior accuracy, underscoring its potential as a robust solution for federated learning in autonomous vehicles. Collectively, these examples highlight the critical role of federated learning frameworks and algorithms in advancing the capabilities of autonomous systems while maintaining data security and efficiency [39, 40].

4 Reinforcement Learning for Resource Management

4.1 Integration with Reinforcement Learning

Integrating reinforcement learning (RL) with federated learning (FL) in autonomous vehicle networks enhances resource management and decision-making by optimizing resource efficiency while maintaining high model accuracy and privacy. The RAFLTP framework exemplifies this integration, using RL to improve trajectory prediction in autonomous vehicles, aiding navigation in complex environments [24].

As illustrated in Figure 5, the hierarchical integration of RL with FL focuses on three main areas: resource management, incentive mechanisms, and communication efficiency. Each category highlights specific strategies and frameworks that enhance the performance and efficiency of autonomous vehicle networks. RL enhances FL by enabling adaptive resource allocation through intelligent assignment of model fragments, considering clients' heterogeneous computing and communication capabilities. This approach addresses issues like straggler problems and inefficient resource use, ensuring robust model performance in resource-constrained settings. Techniques such as dynamic updates and intelligent participant selection improve training efficiency, convergence speed, and model quality, effectively tackling challenges from varying client capabilities and data distributions [41, 42, 43, 36, 20]. This integration allows for dynamic adjustments to environmental changes and resource availability, enhancing performance in autonomous vehicle networks.

Furthermore, RL supports reward-based systems that incentivize participation and optimize contributions within FL frameworks. These systems strategically select valuable contributors, improving learning outcomes and resource utilization, addressing challenges such as data heterogeneity and participant availability. This results in higher quality model updates and improved convergence rates, further enriched by economic and game-theoretic incentive mechanisms that encourage data owner participation [43, 5].

Communication efficiency is crucially enhanced by RL-FL integration. Adaptive strategies prioritize optimal device selection and improve data quality, significantly reducing communication overhead. This efficiency accelerates convergence and enhances model accuracy by leveraging shared data and adaptive optimization techniques, addressing challenges posed by heterogeneous client resources and communication constraints [44, 36, 20, 45]. Such improvements are vital in decentralized and asynchronous environments, ensuring high performance across diverse vehicular networks.

Integrating RL with FL forms a robust framework for enhancing resource management and decision-making in autonomous vehicle networks. Adaptive algorithms and innovative frameworks like Resource-Adaptive Asynchronous Federated Learning (Fed-RAA) and dynamic update methods such as FedDUMAP optimize resource utilization across clients with varying computational capabilities. These approaches improve efficiency and reliability in autonomous systems while maintaining high standards of accuracy and data privacy. For instance, Fed-RAA dynamically allocates model fragments based on client resource constraints, while FedDUMAP leverages shared server data and adaptive pruning techniques to enhance training speed and model performance. Collectively, these strategies address challenges related to resource heterogeneity and client participation, leading to more effective and resilient autonomous systems [46, 43, 36, 37, 20].

5 Collaborative Frameworks and Global Policy Sharing

To effectively explore the intricacies of collaborative frameworks in the context of autonomous vehicle networks, it is essential to first examine the mechanisms that facilitate coalition formation and global policy sharing. This foundational understanding will provide insight into how these frameworks operate in practice, ultimately enhancing the performance and efficiency of federated learning systems. The subsequent subsection will delve into the specific strategies employed in the formation of collaborative frameworks and the implications for coalition dynamics.

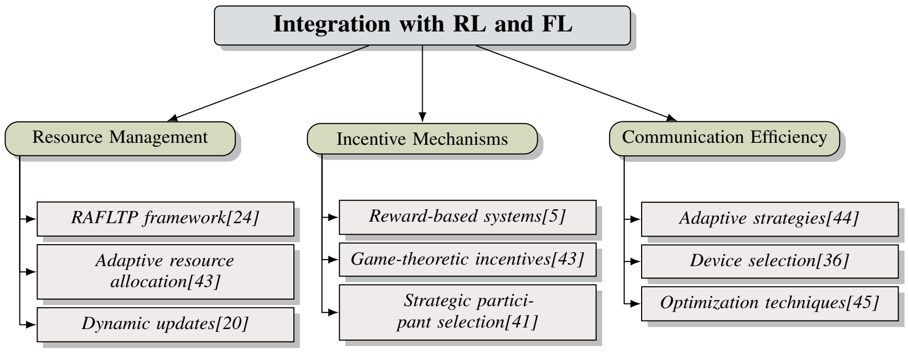


Figure 5: This figure illustrates the hierarchical integration of reinforcement learning with federated learning, focusing on three main areas: resource management, incentive mechanisms, and communication efficiency. Each category highlights specific strategies and frameworks that enhance the performance and efficiency of autonomous vehicle networks.

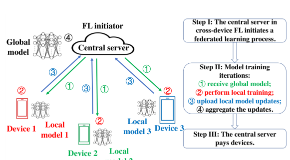
5.1 Collaborative Frameworks and Coalition Formation

The formation of collaborative frameworks and coalitions in federated learning (FL) environments is crucial for enhancing the performance and efficiency of autonomous vehicle networks. These frameworks facilitate global policy sharing, enabling autonomous vehicles to benefit from collective intelligence while preserving data privacy. One innovative approach involves creating non-overlapping collaboration coalitions among clients, allowing them to collaborate with those who maximize their model performance [47]. This strategy ensures that vehicles are grouped in coalitions that optimize learning outcomes, thus enhancing the overall system performance.

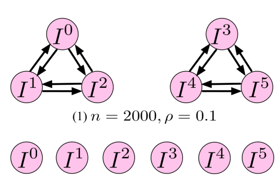
To address communication challenges inherent in autonomous vehicle networks, hierarchical frameworks that integrate advanced methodologies such as UAV trajectory planning have been proposed. These frameworks mitigate communication issues, thereby enhancing collaboration among vehicles [48]. By optimizing the trajectories of unmanned aerial vehicles (UAVs), the frameworks ensure efficient data exchange and robust connectivity, which are essential for effective coalition formation and global policy sharing.

Ensuring fairness and equitable participation in collaborative frameworks is another critical aspect. The Collaborative Fairness Federated Learning (CFFL) method effectively identifies and isolates free-riders, ensuring that only contributing participants benefit from the collaborative model [49]. This approach prevents exploitation within the coalition, promoting a fair and balanced learning environment where all participants are incentivized to contribute meaningfully.

The comparison of various FL frameworks, such as PaddleFL, TensorFlow Federated, FATE, and PySyft, highlights the diverse strategies employed to address challenges related to data privacy, security, and performance [17]. Each framework offers unique strengths and weaknesses, enabling the customization of coalition formation strategies to suit the specific needs of autonomous vehicle networks.



(a) Federated Learning (FL) across Devices[50]



(b) The image shows a network of interconnected nodes, each labeled with a unique identifier (I0, I1, I2, I3, I4, I5).[47]

Parameters	Values
Dataset	MNIST
Neural network	CNN
Activation function	ReLu
FL algorithm	FedAvg
Number of clients	20
Number of rounds	50

(c) Parameters and Values for a Machine Learning Experiment[51]

Figure 6: Examples of Collaborative Frameworks and Coalition Formation

As shown in Figure 6, The concept of "Collaborative Frameworks and Global Policy Sharing; Collaborative Frameworks and Coalition Formation" is vividly illustrated through a series of examples that highlight the intricate processes and structures involved in federated learning and coalition dynamics. The first example focuses on Federated Learning (FL) across devices, showcasing a flowchart that elucidates the decentralized training process. Here, a central server orchestrates the learning by distributing a global model to various local devices, which then train these models independently. The locally trained models are subsequently aggregated back at the central server to refine the global model iteratively. This method emphasizes the collaborative nature of federated learning, where multiple devices contribute to a shared goal while maintaining data privacy. The second example illustrates a network of interconnected nodes, each uniquely identified, symbolizing the complex web of relationships and data exchanges in a collaborative network. This visual representation underscores the importance of connectivity and communication in forming effective coalitions. Lastly, a detailed table of parameters and values used in a machine learning experiment provides insight into the technical specifications that underpin these collaborative frameworks. This structured data presentation includes key aspects such as datasets, neural network architectures, and specific algorithms, offering a glimpse into the experimental setups that drive innovation in federated learning and coalition formation. Together, these examples provide a comprehensive overview of how collaborative frameworks and global policy sharing can be effectively implemented and analyzed in modern technological environments. [**?**]zhang2022enablinglongtermcooperationcrosssilo,cui2022collaborationequilibriumfederatedlearning,liu2024potentialgamepersp

5.2 Decentralized Federated Learning with Blockchain

The integration of blockchain technology into decentralized federated learning frameworks represents a significant advancement in enhancing trust mechanisms and ensuring secure data exchanges among client nodes. Blockchain's inherent properties of immutability and transparency make it an ideal solution for addressing the trust issues prevalent in decentralized federated learning environments [52]. By employing distributed ledger technology, blockchain facilitates secure and verifiable transactions, allowing for the seamless sharing of model updates while preserving data privacy.

The Zero-X framework leverages blockchain technology to enable decentralized federated learning, particularly in enhancing trust mechanisms for the detection of cyberattacks [53]. This framework utilizes blockchain's decentralized nature to ensure that all participating nodes can verify the integrity of shared data, thereby mitigating risks associated with malicious activities and ensuring a robust defense against cyber threats.

Moreover, the Secure and Reliable Blockchain-based Federated Learning (SRB-FL) framework exemplifies the use of blockchain smart contracts to implement incentive mechanisms that encourage participation and enhance trust among federated learning devices [35]. By automating the execution of agreements and ensuring compliance, smart contracts provide a reliable means of managing contributions and rewards, thus fostering a collaborative environment where data integrity and security are prioritized.

The integration of blockchain technology into federated learning systems significantly enhances their privacy and security by utilizing decentralized consensus algorithms and encryption for secure transactions among participants, while simultaneously improving scalability through efficient data management and minimizing dependence on centralized authorities. This approach addresses critical challenges such as data reliability and model aggregation, enabling a more robust and trustworthy collaborative training environment across various applications, including industrial, vehicular, and healthcare sectors. [54, 55, 35]. This decentralized approach ensures that all transactions are recorded in a tamper-proof manner, providing an auditable trail that enhances accountability and trust among participants.

6 Challenges and Future Directions

Advancing federated learning (FL) in autonomous vehicle networks requires tackling complex challenges in data management and model performance, specifically data heterogeneity and model staleness. These issues impede FL system effectiveness, necessitating robust solutions for dynamic environments. The following subsection delves into these challenges, their impact on FL processes, and potential mitigation strategies.

AI-generated, for reference only.

6.1 Data Heterogeneity and Model Staleness

Data heterogeneity and model staleness pose significant hurdles in FL, especially within autonomous vehicle networks, where non-IID client data complicates model aggregation, degrading overall system performance. Diverse data distributions can lead to inefficient model updates, while asynchronous client updates exacerbate model staleness, resulting in suboptimal outcomes [56]. Addressing these challenges requires innovative strategies to manage diverse data environments and mitigate model staleness. While the FEDLGD method is effective in certain contexts, its increased communication and computation costs limit scalability [57]. Similarly, the FedGBO algorithm shows promise for adaptive FL with objective-modifying algorithms, yet further research is necessary to enhance its effectiveness with heterogeneous data [56].

The GFCL framework, which uses a GRU-based federated continual learning approach, addresses data heterogeneity by predicting future data sequences but may struggle with limited data or high heterogeneity, requiring further refinement [26]. Hierarchical federated learning with quantization techniques aims to reduce communication overhead by compressing model updates; however, the large size of deep learning models and long communication delays remain hurdles that can impede convergence rates [19]. Moreover, the performance of hybrid federated learning methods may be affected by server dataset size and quality, as well as communication bandwidth, highlighting the need for efficient resource allocation and bandwidth management strategies [58]. Future research should focus on optimizing learning efficiency, enhancing data privacy, and integrating complex neural network structures. Additionally, understanding FL's environmental impact, particularly regarding carbon emissions, is crucial for sustainable development in intelligent transportation systems, ultimately bolstering the robustness and efficiency of FL systems in autonomous vehicle networks.

6.2 Scalability and Resource Management

Scalability and resource management are crucial for deploying FL in autonomous vehicles, where diverse network conditions and varying computational capabilities present significant challenges. The FedAVO framework enhances scalability and speed, particularly in privacy-preserving and real-time contexts, by improving communication efficiency and reducing computational overhead [59]. However, its effectiveness may be compromised under highly variable network conditions or when mobile devices exhibit differing computational capabilities [60]. Implementing bi-level optimization frameworks like SPIDER poses additional challenges due to significant computational overhead during architecture search processes [61]. Approaches like FedMA, involving parameter matching across numerous clients and layers, encounter computational complexity issues that can slow performance in large-scale scenarios [62].

In FL environments, unreliable clients and malicious activities threaten model integrity, necessitating robust strategies to safeguard privacy and security [63]. Although methods have been developed to enhance FL system resilience against certain attacks, they may remain vulnerable to sophisticated threats, particularly in networks with a high proportion of unreliable clients [64]. Resource management strategies must also consider deploying large foundation models on resource-constrained edge devices, where even compressed models may be unsuitable [33]. The assumption that local models are subsets of a global model can limit FL system flexibility, highlighting the need for adaptable frameworks accommodating diverse model architectures [13].

Innovative approaches that enhance communication efficiency and reduce computational overhead are essential. Revisiting communication-efficient strategies can lead to faster convergence and improved prediction accuracy, optimizing resource utilization in FL applications [65]. By implementing these strategies, FL can scale effectively across autonomous vehicle networks, enhancing decision-making capabilities and overall performance.

6.3 Future Directions and Research Opportunities

Advancing FL and reinforcement learning (RL) in autonomous vehicle systems presents numerous research opportunities aimed at enhancing system efficiency, adaptability, and security. A critical area for future exploration involves refining model partitioning strategies to better align with client resource constraints, particularly for complex model architectures such as large language models [20].

This refinement can improve FL framework scalability and adaptability, ensuring robust performance across diverse vehicular environments.

Future research should also focus on comprehensive evaluation methodologies and theoretical advancements for handling non-IID data distributions, as well as techniques for managing multimodal data and improving communication efficiency in FL. The potential of adaptive optimization techniques, exemplified by the FedGBO algorithm's fast convergence rates and reduced communication and computation costs, underscores the need for continued innovation [56]. Additionally, refining methods to manage label sparsity and exploring advanced model compression techniques are essential for reducing costs and improving efficiency [66]. Enhancing privacy-preserving data generation techniques and improving the distillation process efficiency are vital for ensuring privacy and security concerns are adequately addressed [57].

Exploring server-client communication patterns and optimizing hybrid federated learning frameworks, such as FedCLG, will be crucial for improving scalability and adaptability in dynamic environments [58]. Enhancing model adaptability to various attacks and investigating additional features for anomaly detection can bolster the robustness and security of autonomous vehicle systems [26]. Incentive mechanisms and extending algorithms like DFP to improve adaptability and performance in diverse traffic scenarios are promising areas for future research [23]. Expanding benchmarks to include more diverse driving conditions and refining federated learning algorithms to enhance model robustness and generalization capabilities will be essential for advancing FL in autonomous driving contexts [67].

Finally, improving benchmarks, enhancing interpretability, exploring decentralized aggregation techniques, and applying FL to distributed intelligent systems are identified as key future research directions [17]. By addressing these opportunities, FL and RL can evolve, paving the way for more intelligent, efficient, and secure autonomous vehicle systems.

7 Conclusion

The exploration of federated learning (FL) and reinforcement learning (RL) within this survey underscores their pivotal role in revolutionizing autonomous vehicle systems. FL's decentralized model training paradigm effectively addresses pressing concerns related to data privacy and communication efficiency by facilitating collaborative learning among autonomous vehicles without necessitating the exchange of raw data. This methodology not only ensures privacy protection but also optimizes resource management, thereby augmenting the decision-making prowess of intelligent transportation systems.

The incorporation of RL into FL frameworks enhances the adaptability and responsiveness of autonomous vehicles, particularly in dynamic environments. RL's ability to derive optimal policies through interaction with the environment refines control strategies and decision-making processes in complex driving scenarios. This integration is crucial for optimizing resource allocation, ultimately improving the efficiency and safety of autonomous driving systems.

Despite these advancements, the survey highlights persistent challenges such as data heterogeneity, model staleness, and scalability issues, which call for innovative solutions to ensure robust and efficient FL implementations in vehicular networks. Addressing these challenges through adaptive frameworks and sophisticated algorithms is vital for harnessing the full potential of FL and RL in autonomous vehicle applications.

Ongoing research and development are essential to overcome these challenges and unlock new possibilities in FL and RL. Progress in these areas will empower researchers and practitioners to develop more efficient, reliable, and safer autonomous driving solutions, significantly enhancing the performance and safety of intelligent transportation systems.

References

[1] Latif U. Khan, Yan Kyaw Tun, Madyan Alsenwi, Muhammad Imran, Zhu Han, and Choong Seon Hong. A dispersed federated learning framework for 6g-enabled autonomous driving cars, 2021.

[2] Shiying Zhang, Jun Li, Long Shi, Ming Ding, Dinh C. Nguyen, Wuzheng Tan, Jian Weng, and Zhu Han. Federated learning in intelligent transportation systems: Recent applications and open problems, 2023.

[3] Keith Bonawitz, Hubert Eichner, Wolfgang Grieskamp, Dzmitry Huba, Alex Ingerman, Vladimir Ivanov, Chloe Kiddon, Jakub Konečný, Stefano Mazzocchi, Brendan McMahan, et al. Towards federated learning at scale: System design. *Proceedings of machine learning and systems*, 1:374–388, 2019.

[4] Federated deep learning meets autonomous vehicle perception: Design and verification.

[5] Xuezhen Tu, Kun Zhu, Nguyen Cong Luong, Dusit Niyato, Yang Zhang, and Juan Li. Incentive mechanisms for federated learning: From economic and game theoretic perspective, 2021.

[6] Keith Bonawitz, Hubert Eichner, Wolfgang Grieskamp, Dzmitry Huba, Alex Ingerman, Vladimir Ivanov, Chloe Kiddon, Jakub Konečný, Stefano Mazzocchi, H. Brendan McMahan, Timon Van Overveldt, David Petrou, Daniel Ramage, and Jason Roselander. Towards federated learning at scale: System design, 2019.

[7] Ahmet M. Elbir, Burak Soner, Sinem Coleri, Deniz Gunduz, and Mehdi Bennis. Federated learning in vehicular networks, 2022.

[8] Xianke Qiang, Zheng Chang, Chaoxiong Ye, Timo Hamalainen, and Geyong Min. Split federated learning empowered vehicular edge intelligence: Adaptive parellel design and future directions, 2024.

[9] Latif U. Khan, Ehzaz Mustafa, Junaid Shuja, Faisal Rehman, Kashif Bilal, Zhu Han, and Choong Seon Hong. Federated learning for digital twin-based vehicular networks: Architecture and challenges, 2022.

[10] Rui Song, Lingjuan Lyu, Wei Jiang, Andreas Festag, and Alois Knoll. V2x-boosted federated learning for cooperative intelligent transportation systems with contextual client selection, 2023.

[11] Wissam Kontar, Xinzhi Zhong, and Soyoung Ahn. Learning driver models for automated vehicles via knowledge sharing and personalization, 2023.

[12] Levente Alekszejenkó and Tadeusz Dobrowiecki. A v2x-based privacy preserving federated measuring and learning system, 2024.

[13] Boyu Fan, Siyang Jiang, Xiang Su, Sasu Tarkoma, and Pan Hui. A survey on model-heterogeneous federated learning: Problems, methods, and prospects, 2024.

[14] Amirhossein Reisizadeh, Isidoros Tziotis, Hamed Hassani, Aryan Mokhtari, and Ramtin Pedarsani. Straggler-resilient federated learning: Leveraging the interplay between statistical accuracy and system heterogeneity, 2020.

[15] Tian Li, Anit Kumar Sahu, Ameet Talwalkar, and Virginia Smith. Federated learning: Challenges, methods, and future directions. *IEEE signal processing magazine*, 37(3):50–60, 2020.

[16] Bart Cox, Lydia Y. Chen, and Jérémie Decouchant. Aergia: Leveraging heterogeneity in federated learning systems, 2022.

[17] Ji Liu, Jizhou Huang, Yang Zhou, Xuhong Li, Shilei Ji, Haoyi Xiong, and Dejing Dou. From distributed machine learning to federated learning: A survey, 2022.

[18] Mohak Chadha, Pulkit Khera, Jianfeng Gu, Osama Abboud, and Michael Gerndt. Training heterogeneous client models using knowledge distillation in serverless federated learning, 2024.

[19] Lumin Liu, Jun Zhang, Shenghui Song, and Khaled B. Letaief. Hierarchical federated learning with quantization: Convergence analysis and system design, 2023.

AI-generated, for reference only.

[20] Ruirui Zhang, Xingze Wu, Yifei Zou, Zhenzhen Xie, Peng Li, Xiuzhen Cheng, and Dongxiao Yu. A resource-adaptive approach for federated learning under resource-constrained environments, 2024.

[21] Haibo Yang, Peiwen Qiu, Prashant Khanduri, Minghong Fang, and Jia Liu. Understanding server-assisted federated learning in the presence of incomplete client participation, 2024.

[22] Hong Zhang, Ji Liu, Juncheng Jia, Yang Zhou, Huaiyu Dai, and Dejing Dou. Fedduap: Federated learning with dynamic update and adaptive pruning using shared data on the server, 2022.

[23] Tengchan Zeng, Omid Semiari, Mingzhe Chen, Walid Saad, and Mehdi Bennis. Federated learning on the road: Autonomous controller design for connected and autonomous vehicles, 2022.

[24] Weiliang Chen, Li Jia, Yang Zhou, and Qianqian Ren. Reputation-driven asynchronous federated learning for enhanced trajectory prediction with blockchain, 2024.

[25] Ahmet M. Elbir, Sinem Coleri, Anastasios K. Papazafeiropoulos, Pandelis Kourtessis, and Symeon Chatzinotas. A hybrid architecture for federated and centralized learning, 2022.

[26] Anum Talpur and Mohan Gurusamy. Gfcl: A gru-based federated continual learning framework against data poisoning attacks in iov, 2022.

[27] Yu Xianjia, Jorge Peña Queralta, Jukka Heikkonen, and Tomi Westerlund. An overview of federated learning at the edge and distributed ledger technologies for robotic and autonomous systems, 2021.

[28] Jayprakash S. Nair, Divya D. Kulkarni, Ajitem Joshi, and Sruthy Suresh. On decentralizing federated reinforcement learning in multi-robot scenarios, 2022.

[29] Zijian Zhang, Shuai Wang, Yuncong Hong, Liangkai Zhou, and Qi Hao. Distributed dynamic map fusion via federated learning for intelligent networked vehicles, 2022.

[30] Tianhao Wu, Mingzhi Jiang, Yinhui Han, Zheng Yuan, and Lin Zhang. Density-aware federated imitation learning for connected and automated vehicles with unsignalized intersection, 2021.

[31] Balqees Talal Hasan and Ali Kadhum Idrees. Federated learning for iot/edge/fog computing systems, 2024.

[32] Lingjuan Lyu, Jiangshan Yu, Karthik Nandakumar, Yitong Li, Xingjun Ma, Jiong Jin, Han Yu, and Kee Siong Ng. Towards fair and privacy-preserving federated deep models, 2020.

[33] Sixing Yu, J. Pablo Muñoz, and Ali Jannesari. Bridging the gap between foundation models and heterogeneous federated learning, 2023.

[34] Kate Donahue and Jon Kleinberg. Optimality and stability in federated learning: A game-theoretic approach, 2021.

[35] Hajar Moudoud, Soumaya Cherkaoui, and Lyes Khoukhi. Towards a secure and reliable federated learning using blockchain, 2022.

[36] Ji Liu, Juncheng Jia, Hong Zhang, Yuhui Yun, Leye Wang, Yang Zhou, Huaiyu Dai, and Dejing Dou. Efficient federated learning using dynamic update and adaptive pruning with momentum on shared server data, 2024.

[37] Junhyung Lyle Kim, Mohammad Taha Toghani, César A. Uribe, and Anastasios Kyrillidis. Adaptive federated learning with auto-tuned clients, 2024.

[38] Taki Hasan Rafi, Faiza Anan Noor, Tahmid Hussain, Dong-Kyu Chae, and Zhaohui Yang. A generalized look at federated learning: Survey and perspectives, 2023.

[39] Dun Zeng, Siqi Liang, Xiangjing Hu, Hui Wang, and Zenglin Xu. Fedlab: A flexible federated learning framework, 2022.

[40] Gustav A. Baumgart, Jaemin Shin, Ali Payani, Myungjin Lee, and Ramana Rao Kompella. Not all federated learning algorithms are created equal: A performance evaluation study, 2024.

[41] Herbert Woisetschläger, Alexander Isenko, Shiqiang Wang, Ruben Mayer, and Hans-Arno Jacobsen. Federated fine-tuning of llms on the very edge: The good, the bad, the ugly, 2024.

[42] Mohamed Yassine Boukhari, Akash Dhasade, Anne-Marie Kermarrec, Rafael Pires, Othmane Safsafi, and Rishi Sharma. Boosting federated learning in resource-constrained networks, 2023.

[43] Ahmed M. Abdelmoniem, Atal Narayan Sahu, Marco Canini, and Suhaib A. Fahmy. Resource-efficient federated learning, 2022.

[44] Nader Bouacida, Jiahui Hou, Hui Zang, and Xin Liu. Adaptive federated dropout: Improving communication efficiency and generalization for federated learning, 2020.

[45] Xiangyi Chen, Xiaoyun Li, and Ping Li. Toward communication efficient adaptive gradient method, 2021.

[46] Isidoros Tziotis, Zebang Shen, Ramtin Pedarsani, Hamed Hassani, and Aryan Mokhtari. Straggler-resilient personalized federated learning, 2022.

[47] Sen Cui, Jian Liang, Weishen Pan, Kun Chen, Changshui Zhang, and Fei Wang. Collaboration equilibrium in federated learning, 2022.

[48] Chong Huang, Gaojie Chen, Pei Xiao, Jonathon A. Chambers, and Wei Huang. Fair resource allocation for hierarchical federated edge learning in space-air-ground integrated networks via deep reinforcement learning with hybrid control, 2024.

[49] Lingjuan Lyu, Xinyi Xu, and Qian Wang. Collaborative fairness in federated learning, 2020.

[50] Ning Zhang, Qian Ma, and Xu Chen. Enabling long-term cooperation in cross-silo federated learning: A repeated game perspective, 2022.

[51] Kang Liu, Ziqi Wang, and Enrique Zuazua. A potential game perspective in federated learning, 2024.

[52] Ehsan Hallaji, Roozbeh Razavi-Far, Mehrdad Saif, Boyu Wang, and Qiang Yang. Decentralized federated learning: A survey on security and privacy, 2024.

[53] Abdelaziz Amara korba, Abdelwahab Boualouache, and Yacine Ghamri-Doudane. Zero-x: A blockchain-enabled open-set federated learning framework for zero-day attack detection in iov, 2024.

[54] Nanqing Dong, Zhipeng Wang, Jiahao Sun, Michael Kampffmeyer, William Knottenbelt, and Eric Xing. Defending against poisoning attacks in federated learning with blockchain, 2024.

[55] Haemin Lee and Joongheon Kim. Trends in blockchain and federated learning for data sharing in distributed platforms, 2021.

[56] Jed Mills, Jia Hu, Geyong Min, Rui Jin, Siwei Zheng, and Jin Wang. Accelerating federated learning with a global biased optimiser, 2022.

[57] Chun-Yin Huang, Ruinan Jin, Can Zhao, Daguang Xu, and Xiaoxiao Li. Federated virtual learning on heterogeneous data with local-global distillation, 2023.

[58] Jieming Bian, Lei Wang, Kun Yang, Cong Shen, and Jie Xu. Accelerating hybrid federated learning convergence under partial participation, 2024.

[59] Md Zarif Hossain and Ahmed Imteaj. Fedavo: Improving communication efficiency in federated learning with african vultures optimizer, 2023.

[60] Pavana Prakash, Jiahao Ding, Maoqiang Wu, Minglei Shu, Rong Yu, and Miao Pan. To talk or to work: Delay efficient federated learning over mobile edge devices, 2021.

[61] Erum Mushtaq, Chaoyang He, Jie Ding, and Salman Avestimehr. Spider: Searching personalized neural architecture for federated learning, 2021.

[62] Hongyi Wang, Mikhail Yurochkin, Yuekai Sun, Dimitris Papailiopoulos, and Yasaman Khazaeni. Federated learning with matched averaging, 2020.

[63] Chuan Ma, Jun Li, Ming Ding, Howard Hao Yang, Feng Shu, Tony Q. S. Quek, and H. Vincent Poor. On safeguarding privacy and security in the framework of federated learning, 2020.

[64] Chuan Ma, Jun Li, Ming Ding, Kang Wei, Wen Chen, and H. Vincent Poor. Federated learning with unreliable clients: Performance analysis and mechanism design, 2021.

[65] Zhigang Yan, Dong Li, Zhichao Zhang, and Jiguang He. Revisiting communication-efficient federated learning with balanced global and local updates, 2022.

[66] Ibrahim Abdul Majeed, Sagar Kaushik, Aniruddha Bardhan, Venkata Siva Kumar Tadi, Hwang-Ki Min, Karthikeyan Kumaraguru, and Rajasekhara Duvvuru Muni. Comparative assessment of federated and centralized machine learning, 2022.

[67] Lidia Fantauzzo, Eros Fanì, Debora Caldarola, Antonio Tavera, Fabio Cermelli, Marco Ciccone, and Barbara Caputo. Feddrive: Generalizing federated learning to semantic segmentation in autonomous driving, 2023.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.

AI-generated, for reference only.