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Decentralized Perception: A Systematic Review of Federated Learning for Privacy-Preserving Detection of Mixed Road Users in Intelligent Transportation Systems (ITS)

Chijiuka F. Akuma[a], Pradeep Hewage[a], Tighe Bren[a], Basil O. Nwozaku[a] and Amarachi Eche[a]

[a]Centre for Applied Computer Science, School of Arts & Creative Technologies, University of Greater Manchester, Bolton, United Kingdom

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ABSTRACT

The increasing complexity of urban environments, characterised by diverse mix of vehicles, and vulnerable road users such as pedestrians, and cyclists, poses significant safety and efficiency challenges for modern transportation. Intelligent Transportation Systems (ITS) aim to mitigate these issues, but the existing centralised models for road user detection face critical limitations regarding data privacy, latency, and scalability. Federated Learning (FL) has emerged as a promising decentralized paradigm to overcome these challenges by training models collaboratively without sharing raw data. This review followed the systematic literature review (SLR) methodology, with a comprehensive search of academic and scholarly databases and systematically analysed the current state of research on the application of Federated Learning in ITS for detecting mixed road users. Also examined in this work is the evolution of intelligent transport systems from centralized to decentralized and edge-based detection architectures, analyses the principles and advantages of Federated Learning, and explore the key scholarly debates surrounding its implementation, including the trade-offs between privacy and performance, data heterogeneity, and the gap between simulation and real-world deployment. This review highlights significant research gaps in the application of Federated Learning specifically for the task detection and classifications of vulnerable road user (VRU) in a mixed-user transport setting. The potential of Federated learning to enhance road safety through timely alert mechanism was explored, and the recommendations included that future research should consider among other things the creation of federated learning frameworks that are able to detect and classify different road users in a mixed road setting.

1. Introduction

Growing urbanisation and rising vehicle ownership have created significant challenges for modern transportation. Road networks face increasing congestion and complexity, making it difficult to safely and efficiently manage a diverse mix of users, which includes cars, buses, motorcycles, bicycles, and pedestrians. To address this critical issues, Intelligent Transportation Systems (ITS) are being adopted to help and improve traffic flow, safety, and overall transportation management (Khatua *et al.*, 2024). The adoption of advanced computational models such as AI and deep learning (DL), and sensor technologies has revolutionised autonomous driving and intelligent transportation, thus reshaping modern transportation through promising safer roads, smoother traffic, and reduced environmental

* Corresponding author. Tel.: +2349068786588
E-mail address: cfa2crt@bolton.ac.uk (Chijiuka. F. Akuma)
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impact. These technologies enable vehicles to perceive and interpret their environment through object detection and tracking. However, current centralized exhibit critical limitations. These limitations include that they are expensive to develop, create data privacy worries, and don't scale up well, especially in the fast-moving, and unpredictable real-life traffic (Shao *et al.*, 2024)**.** These limitations necessitate a more collaborative and privacy-preserving approach to data processing within ITS.

The strengths of intelligent transport system have also been enhanced by Advanced Driver Assistance Systems (ADAS), and Cyber-Physical Systems (CPS). These systems use a mix of sensors and machine learning algorithms to make sure a vehicle accurately spots everything nearby. However, achieving an optimal balance between detection accuracy, processing latency, and computational efficiency remains a challenge (Ayachi *et al.*, 2025).

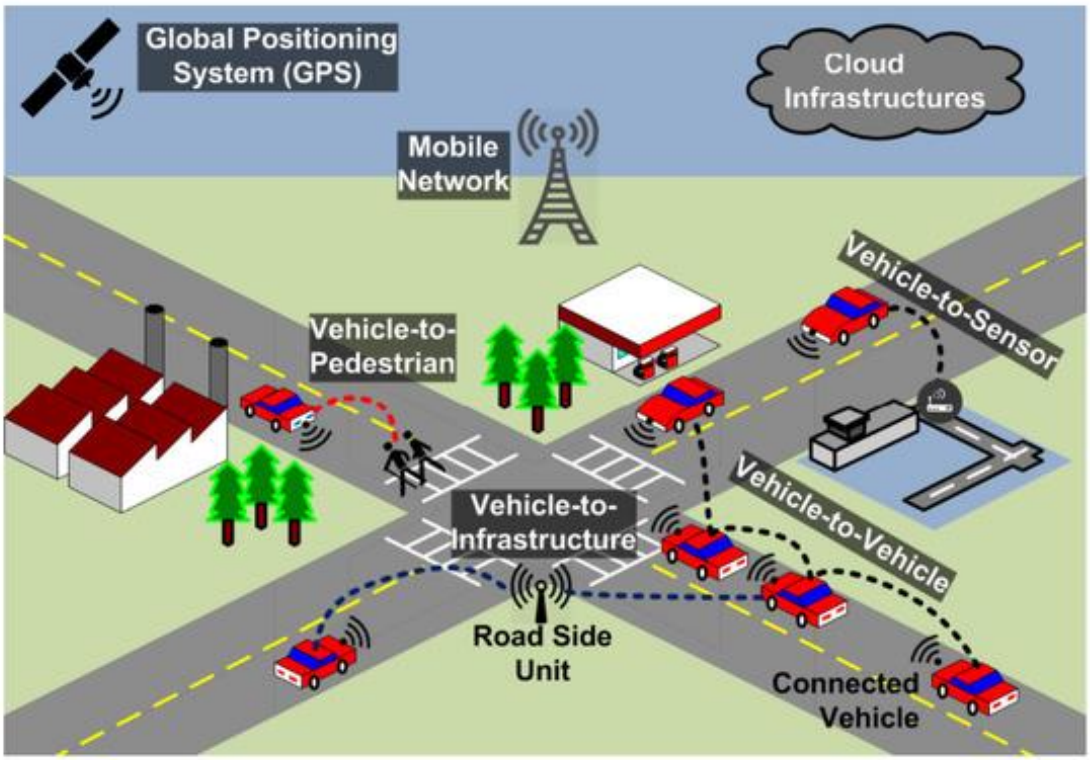


Figure 1: Internet of Vehicles(Avcı & Koca, 2024).

The Internet of Vehicles (IoV), as shown in Figure , is an integral component of intelligent transport system is responsible for real-time exchange of data between vehicles and other road infrastructures (**V2I**). This transfer of data supports applications such as adaptive traffic monitoring, collision avoidance, predictive maintenance, and dynamic route planning systems. Internet of vehicles (IoT) has contributed to smart cities in several ways. One is the provision of system that addresses the rising cases of traffic accidents, vehicle growth, and environmental concerns thus, fostering a collaborative ecosystem for safer and more efficient transportation (Ullah et al., 2025; Wu et al., 2023). Despite this technological growth, statistics shows that road traffic accidents is still a major global public concern. For instance, in 2021, approximately 1.19 million traffic related deaths occurred worldwide, making traffic injuries the 12th leading cause of death across all age groups. In the statistics, pedestrians account for 23% of fatalities, cyclists and personal micro-mobility users represent 6% and 3%, respectively, and two and three wheeled vehicle users contributed 21% of the road deaths. Aside death, the economic impact of traffic accidents is also significant, with a projected global cost of US$1.8 trillion between 2015 and 2030 (Silva *et al.*, 2025). One thing that is standing out is that vulnerable road users (VRUs), such as pedestrians, cyclists, and motorcyclists, constitute a growing proportion of fatalities, with most of the fatalities happening at road intersections, which are critical nodes within urban road networks. In 2022, intersections accounted for 16% of pedestrian fatalities, 29% of cyclist deaths, and 36% of motorcyclist deaths (Shang *et al.*, 2025). These figures highlight the need for an effective detection and monitoring system of VRUs to reduce fatalities and enhance road safety.

Federated Learning (FL) has emerged as a promising solution to overcome the challenges identified to be associated with the existing centralised models. In FL, multiple clients collaboratively train a shared model without exchanging raw data. This decentralised method ensures that privacy is preserved, and reduces communication cost while maintaining model accuracy (Djenouri et al., 2024; Hallak & Kem, 2025; Khatua et al., 2024)

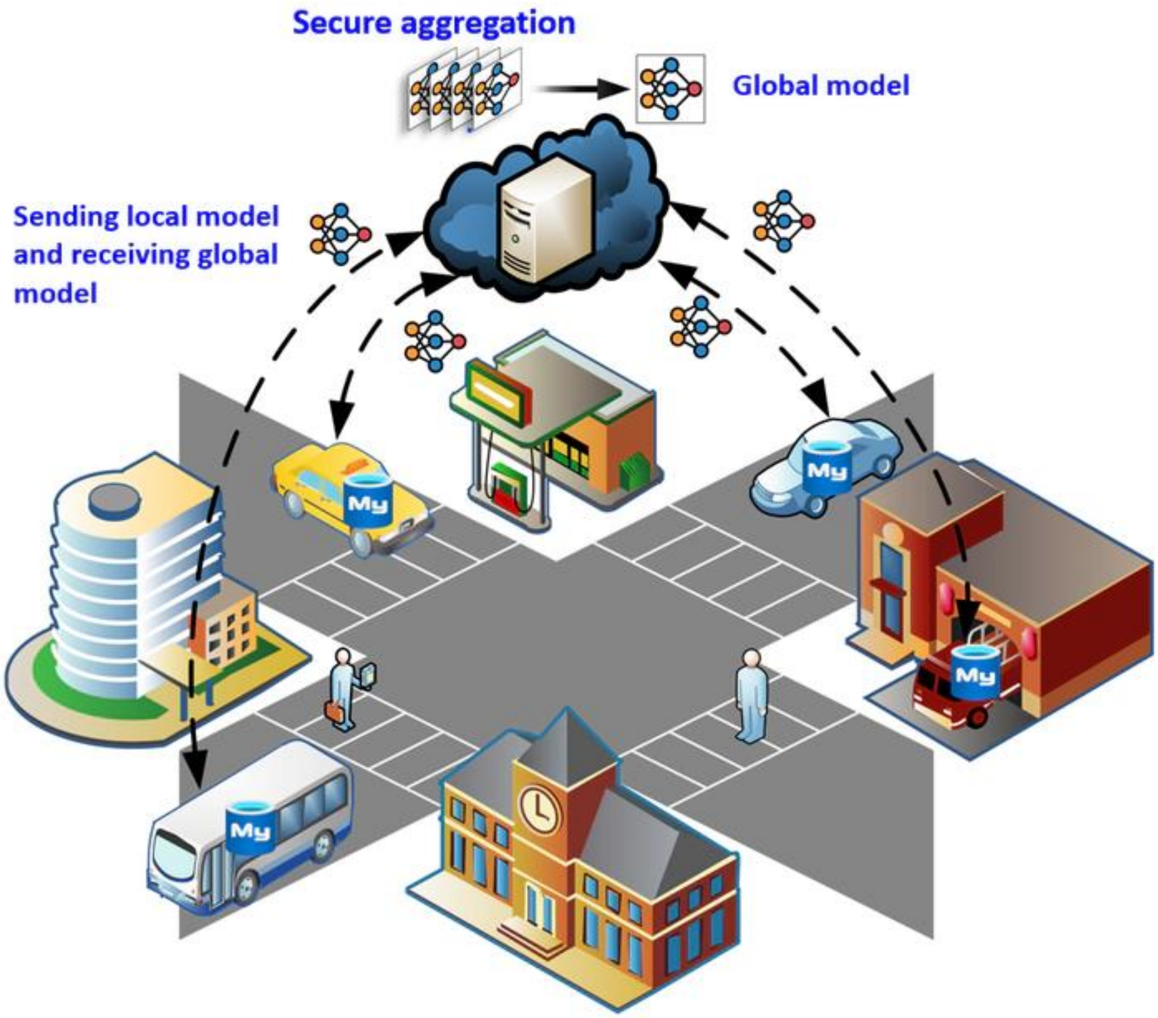


Figure 1: Federated Learning (Chellapandi et al., 2023).

FL's ability to support distributed intelligence across heterogeneous edge devices makes it suitable for applications in ITS. Other areas the studies also explored is the application of FL in autonomous driving and smart transportation (Alqubaysi et al., 2025; T. Li et al., 2020). As shown in Figure 1, the core of federated learning communication process involves clients sending local model updates to the server, and the server performs secure aggregation, and then sends the global model back to the clients. However, existing research primarily focuses on vehicle detection or traffic prediction in structured environments. Limited studies address the detection and classification of mixed road users through federated learning in heterogeneous urban settings. Moreover, the interpretation of "real-time" detection in such frameworks remains ambiguous, particularly concerning latency and communication trade-offs. Therefore, this paper aims to provide a systematic review of the existing and current stage of research in the application of Federated learning in Intelligent transport system and highlight areas for future research.

In recent years, vehicles have increasingly been equipped with sensors and Information and Communication Technology (ICT) capabilities for data collection and intervehicle communication (Walch et al., 2025).
Integrating state-of-the-art technologies like AI, data analytics, and the Internet of Things (IoT) into transportation networks aims to increase their efficiency, security, and longevity. ITS creates a networked and integrated transportation system that is adaptable to the needs of its users by providing a more accurate, up to the minute data about the traffic (Nagappan et al., 2024).

Recent work in Intelligent Transportation Systems (ITS) has moved beyond simply improving road infrastructure to examining how connected sensors, communication networks, and AI can work together to make transport systems more responsive and safer for all users. Walch, Schirrer and Neubauer, 2025) note that modern vehicles now serve as mobile sensing units, constantly collecting and exchanging data within the traffic environment. This shift has encouraged researchers to look more closely at how such data can support real-time perception and decision-making. Intelligent transport system (ITS) uses different technologies to guarantee traffic efficiency, safety, and sustainability especially in smart cities. These technologies make use of advanced communication, sensing, and data processing technologies to enable real-time decision making and automation of transport and traffic flow. A growing body of studies focuses on the role of Vehicle-to-Everything (V2X) communication and its contribution to cooperative safety. For example, Elassy et al., 2024) and Nagappan, Maheswari and Siva, (2024) show how vehicular networks and roadside devices enable data sharing for tasks such as object detection and collision avoidance.
ITS utilised these components to watch the roads non-stop and tweaks it on the go. From speed boards that drop a few mph, little red lights on slip roads and cameras that spot crashes in seconds are all part of the same Intelligent Transport System. ITS ensure that cars keep moving within the allowable speed limits, spaces cars on the motorway, and ensures that traffic is moved away from trouble before jams grow. With the help of live travel info on your phone, buses are made to stay on time, you avoid queues, and thus travelling quicker, calmer and safer (Thakur & Yousuf, 2023).

Mixed and vulnerable road Users

In many transport studies, the term “mixed road users” (or *mixed traffic*) is used to describe situations where various categories of road users including motorised vehicles, non-motorised vehicles, and vulnerable users such as pedestrians and cyclists share the same roadway or traffic environment. Such arrangements are typically characterised by limited segregation and minimal lane discipline. In several developing countries, these traffic conditions are often referred to as heterogeneous traffic, reflecting the coexistence of vehicles and users with differing physical characteristics and movement patterns interacting within a common road space (Roy & Saha, 2020).
Closely related to this is the concept of vulnerable road users (VRUs), which is widely recognised in transport and road-safety literature. The term generally refers to pedestrians, cyclists, and motorcyclists who, owing to their limited physical protection, are more susceptible to severe injury or fatality in road environments dominated by motor vehicles (Khayesi, 2020).

Vulnerable Road Users (VRUs) a group that includes pedestrians, cyclists, motorcyclists, and other non-motorised users remain the most at risk in modern transport systems. In contrast to vehicle users, VRUs lack protective structures that can protect them during impacts or collisions, thus making even minor road crashes potentially fatal. Dimitrievski et al., (2020) noted that the dynamic and unpredictable movements of VRUs, combined with limited visibility and their inconsistent traffic behaviour, highly raises the likelihood of accidents, especially within mixed traffic. In heterogeneous road systems where motorised and non-motorised users share the same roadway, the absence of clear lane discipline and inadequate separation further increases exposure to danger. Teixeira et al., (2023) emphasise that factors such as poor lighting, driver distraction, and limited sensor perception by autonomous or semi-autonomous vehicles exacerbate the vulnerability of pedestrians and cyclists. These conditions are more prevailing in rapidly urbanising areas, where infrastructure growth most times outpaces the development of safety technologies.

The rising complex nature of urban transportation has necessitated the need for multi-user detection systems capable of identifying and tracking various types of road users simultaneously. The importance of integrating artificial intelligence, the Internet of Things (IoT), and computer vision to enhance situational awareness across transport networks was highlighted in recent studies, such as those by (Z. Zhang et al., 2025) and (Jagatheesaperumal *et al.*,

2024). Multi-user detection allows vehicles, roadside units, and intelligent infrastructure to recognise pedestrians, cyclists, and other non-motorised users in real time, enabling timely collision avoidance responses.
Furthermore, Rahman, Mammeri and Metari, (2025) underscores that the implementation of such systems is central to the development of smart cities, where data from cameras, LiDAR, and radar sensors can be fused to create cooperative safety frameworks. These frameworks not only improve VRU protection, but they also promote efficient management of traffic through adaptive signal control, and risk prediction.

In 2021, an estimated 1.19 million traffic-related deaths happened worldwide. With pedestrians and cyclists accounting for 23% and 6% respectively. Two and three wheeled vehicle users accounted for 21% of the total fatalities. When these traffic accidents happen, they do not just cause deaths but also cause a significant economic burden, with projected costs of US$1.8 trillion between 2015 and 2030 (Silva *et al.*, 2025). Vulnerable road users (VRUs), including pedestrians, cyclists, and motorcyclists, account for many road fatalities, particularly at road intersections, which are high-risk points in transportation. In 2022, 16% of pedestrian deaths, 29% of cyclist deaths, and 36% of motorcyclist deaths happened at road intersections (Shang *et al.*, 2025). In essence, these increasing cases of safety risks faced by VRUs underscore the urgency of deploying multi-user detection technologies as an integral part of transport systems especially in smart cities. By utilising AI-driven perception systems and inter-connected sensing networks, transport systems especially in urban areas can move towards more intelligent, and safer transport systems the different road users (motorised or otherwise) are equally recognised and protected.

Artificial Intelligence and Deep Learning in Intelligent Transport Systems (ITS).

Artificial Intelligence (AI) and Deep Learning (DL) models like Convolutional Neural Networks (CNNs), and You Only Look Once (YOLO) algorithms, have become important in enhancing object detection and classification in Intelligent Transport Systems (ITS). While CNNs pride in effective extraction of hierarchical spatial features from images, which enables them to accurately identify complex patterns, such as vehicles, pedestrians, and cyclists in diverse traffic environments (Choi et al., 2022), YOLO, a real-time object detection framework, in the other hand processes an image in a single pass, simultaneously predicting bounding boxes and class probabilities. This feature of YOLO particularly makes it suitable use in environments where, where rapid detection of multiple road users is very key (Murat & Kiran, 2025). The use of AI and DL in ITS has shown strengths that include high accuracy in object recognition and automation of continuous traffic monitoring and real-time decision-making. The efficiency of detecting objects even in complex traffic conditions are enhanced by these models by integrating data from different sensor types such as cameras, LiDAR, and radar (Mustapha *et al.*, 2025). However, despite the promises, there exists some notable limitations. One of such limitations is that performance of these models heavily depends on large, well-annotated datasets, which can be costly and time-consuming to develop and sometimes violates privacy ethics, especially for heterogeneous traffic environments. These models also find it difficult to generalise well, in mixed traffic situations, where different road users, including vulnerable road users, interact in unpredictable ways (Choi, Ku and Lee, 2022; Mustapha et al., 2025; Saqib et al., 2025). While CNNs and YOLO have shown significant advancements in object detection and classification for ITS, adapting it for the detection and classification of varied road users remain crucial areas for ongoing research.

Detection and classification approaches in ITS.

The integration of perception system in Intelligent Transportation Systems (ITS) have witnessed a significant shift in both architectural design and methodological flow. From remote and powerful processing centres to localised, real-time analytics at the network edge. Examining this trajectory reveals the driving forces behind technological adoption to primarily be the persistent challenges of latency, privacy, and the increasing complexity of urban traffic environments (Herich & Vaščák, 2024).

Traditional centralised detection models.

Many ITS perception pipelines still adopt a centralised architecture in which sensor streams (for example, camera, radar, LiDAR) are forwarded to a remote server or cloud for heavy-weight processing and model inference. Centralised models leverage abundant compute for large-scale model training and make it straightforward to maintain and update a single canonical model, which is beneficial for offline analytics and for training on aggregated, labelled

dataset. Such solutions often use convolutional backbones or region-proposal networks to achieve high detection accuracy when training and deployment conditions are like the datasets used (Cao *et al.*, 2021; Gong *et al.*, 2023).
Despite those strengths, centralised deployments have well-documented weaknesses. First, continuous transfer of high-resolution video or dense point clouds to the cloud causes substantial communication overhead and introduces end-to-end latency that can be unacceptable for safety-critical, real-time tasks such as collision avoidance (Andriulo *et al.*, 2024; Elassy *et al.*, 2024). Second, centralised schemes increase privacy risk because raw, identity-bearing footage leaves the collection site and may conflict with data-protection regulation and public acceptability (Ometov *et al.*, 2022). Third, as the number of sensors grows, cloud costs, bandwidth consumption and single-point failure risks escalate, creating scalability and resilience concerns for city-scale ITS (Andriulo et al., 2024; Cao et al., 2021; Ometov et al., 2022).

A careful review of the existing models reveals that, while centralised models remain attractive for batch analytics and offline training, their latency, privacy and scalability constraints motivate exploration of distributed alternatives that preserve responsiveness, and privacy (Andriulo et al., 2024; Gong et al., 2023).

Decentralised and edge-based detection.

To mitigate the limits of centralised approaches, the ITS research community has increasingly adopted edge and decentralised paradigms. Edge computing places inference (and sometimes training) close to data sources for example on roadside units, smart cameras or in-vehicle processors thereby reducing the need to stream raw data to the cloud and enabling near-real-time reactions. Edge intelligence is particularly attractive for latency-sensitive services and for use cases that combine short-range V2X (vehicle-to-infrastructure) messaging with local perception (Gong et al., 2023; Liang et al., 2024). Decentralised architectures also bring privacy and resilience benefits because raw video need not leave the local domain, and the network is less dependent on a single central server. Recent work shows the potential for combining edge inference with privacy-preserving distributed learning (for example federated learning) so models can be improved collaboratively while raw data remain local a useful property for smart-city deployments worried about legal and social acceptance. However, edge nodes have constrained computing, power and thermal budgets; to operate at scale they therefore require model compression, lightweight architectures and selective offloading policies to maintain a workable accuracy/latency trade-off. Even though decentralised, edge-capable detectors combined with efficient update strategies and privacy-aware learning protocols represent a promising route for responsive, socially acceptable ITS, but they require careful co-design across hardware, algorithms, and communications layers (Gong et al., 2023; M. Li et al., 2025; Liang et al., 2024).

Object detection techniques in mixed traffic.

Modern ITS perception commonly employs families of deep detectors such as YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector) and Faster R-CNN. These families embody different speed/accuracy trade-offs: single-stage detectors (YOLO, SSD) are designed for low latency and are well suited to edge deployment, while two-stage detectors (Faster R-CNN) often yield higher peak accuracy at the expense of longer inference time and heavier computing resources (Ezzeddini et al., 2024; Reddy et al., 2024). Comparative studies in traffic and small-object domains generally show that recent YOLO variants (and lightweight YOLO variants) provide the best balance for real-time edge applications, whereas Faster R-CNN and its compressed variants remain competitive where maximal precision is required.

These detectors have been tailored extensively for vehicle detection, vehicle classification and pedestrian detection under controlled conditions. For vehicle-centred tasks (plate recognition, vehicle count, axle detection) detectors perform strongly when viewpoint and scene conditions align with training data; for pedestrian and cyclist detection, special techniques such as part-aware networks, multispectral inputs and occlusion-handling routines improve robustness but generalisation across scenes remains problematic (Cao et al., 2021; Y. Zhang et al., 2022).
Despite these strengths, the literature and many operational deployments are still biased towards centralised, vehicle-focused perception. Pedestrians and cyclists often smaller, more occluded, and behaviourally more variable than vehicles are under-represented in many datasets and evaluation regimes. This leaves mixed-traffic contexts (common in multimodal urban streets and many low- and middle-income cities) inadequately served by current detection systems. There is therefore a clear need for decentralised, edge-capable detectors explicitly trained and validated for heterogeneous road users and the occlusion/lighting conditions typical of mixed traffic (Cao et al., 2021; Gong et al.,

2023; Y. Zhang et al., 2022).

Federated Learning: Principles and Applications

Federated Learning (FL) has become a promising solution in distributed machine learning. it enables collaborative model training across multiple nodes while ensuring data privacy (R. Zhang, Wang, *et al.*, 2024).

Fundamentals of Federated Learning

Federate Learning operates by training machine learning models locally on client devices, such as vehicles or roadside infrastructures, and aggregating the model updates centrally without sharing the raw data used in training the models. This process starts by initialising a global model, distributing it to clients or nodes, collecting local updates, and aggregating them to refine the global model (Wen *et al.*, 2023; R. Zhang, Mao, *et al.*, 2024). In contrast to traditional centralised machine learning, where data is stored in a central server, FL maintains data locality, thereby enhancing privacy and reducing communication cost (Yurdem *et al.*, 2024)

Types of Federated Learning

Based on data distribution, FL can be classified into three primary types:

i. Horizontal Federated Learning: This type of FL is applied in situations where the clients possess datasets that have the same feature but different samples. An example of scenarios where that can be seen is ITS, where various vehicles collect data that have similar features such as traffic speed, vehicle counts etc, but these data are from different locations (T. Li et al., 2020; C. Zhang et al., 2021).

ii. Vertical Federated Learning: This describes the type of FL utilised when clients have datasets with the same sample set but distinctive features. Although this approach is less common in ITS, it is seen more visible in cases where multiple entities share data about the s entities (e.g., vehicles) but with different attributes (e.g., insurance data vs toll data) (Wen *et al.*, 2023).

iii. Federated Transfer Learning (FTL): This method is a combination of FL with transfer learning to address cases where clients have datasets with different feature and sample sets. This method is very vital for addressing cases where data across clients are heterogeneous and non-IID (Independent and Identically Distributed) (Saha & Ahmad, 2021).

FL in Intelligent Transportation Systems

Federated Learning has shown efficacy especially in addressing transport challenges such as traffic prediction, vehicle detection, and autonomous driving. Recent studies have shown that FL has strong efficacy in these domains, highlighting its potential to enhance model accuracy while preserving data privacy (Liu *et al.*, 2020; R. Zhang, Wang, *et al.*, 2024). However, existing research tend to have focused majorly on vehicle-centric data and applications, with little or no consideration of mixed road users, such as pedestrians and cyclists (Wen *et al.*, 2023; Yurdem *et al.*, 2024). This highlights a potential area for future research into the use of FL in more complex, dynamic multi modal traffic settings.

Advantages and Challenges of FL in ITS

The use of FL in ITS comes with advantages such as:

i. Privacy Preservation: The privacy concerns associated with centralised data storage is addressed by FL by ensuring that data is kept locally and trained on the client's device (Yurdem *et al.*, 2024)

ii. Scalability: With FL, many clients or modes can be accommodated, making it suitable for large-scale ITS deployments (Y. Zhang et al., 2022).

iii. Adaptability: Another promising advantage of Federated learning is that it ensures that machine learning models, can continuously learn and adapt to dynamic traffic conditions in real-time through the continuous update of datasets (T. Li et al., 2020)

Challenges of Federated Learning

Regardless of the numerous benefits of Federated learning, it's application in ITS still faces several challenges:

i. Data Variation: Difference in data distributions across participating clients can cause biasness of model updates and degrade model performance (Saha & Ahmad, 2021; Y. Zhang et al., 2022).
ii. Model Aggregation Bias: The process of combing model updates from the different devices can introduce some biases. These biases often affect the quality of the global model thus reducing the performance accuracy (Yurdem *et al.*, 2024).
iii. Synchronisation Complexity: Coordinating model updates across numerous clients with varying data availability and computational capabilities adds complexity to the training process (Wen *et al.*, 2023).

This research recognises these challenges of FL but aims to show its feasibility and provide insights into its potential applications in multi-modal traffic scenarios through controlled simulation experiments.

Controversies and Debates in Federated Learning and ITS

There have been Significant scholarly debates raised concerning privacy preservation, system performance, adaptability, scalability, and real-world application of Federated learning in intelligent transport systems. With proponents regarding FL as a transformative step towards ethical and privacy-aware artificial intelligence, critics question its true resilience against information leakage and its operational efficiency in heterogeneous vehicular environments (Li et al., 2025).

Privacy vs Performance Trade-off

A major controversy in FL is whether it truly enhances privacy or just redistributes the risks across decentralised nodes. Some researchers have suggested that even though FL prevents direct data sharing, sensitive information may be exposed to extraction from model updates through gradient inversion and model reconstruction attacks (Carletti et al., 2025; Z. Zhou et al., 2024). In other to address these weaknesses of FL, researchers have proposed techniques such as differential privacy, secure aggregation, and homomorphic encryption. However, these techniques even though promising comes at some costs, such as degradation of model accuracy and increased computation (Shi et al., 2016; C. Zhang et al., 2021). Irrespective of the outlined challenges, some scholars still believe that, despite the challenges, FL remains the most promising path to ethically deploy AI in privacy sensitive domains like ITS (Jiang *et al.*, 2020; S. Zhang *et al.*, 2024).

Centralised vs Decentralised Learning

The scholarly debate on centralised and decentralised learning architectures in machine learning highlights a tension between accuracy and privacy. Centralised models proving to outperform FL when complete datasets are available, because they benefit from unified optimisation and low communication latency (Chen *et al.*, 2024). Conversely, decentralised FL systems, ensure that the risk of privacy violations are mitigated by keeping data local to vehicles and edge nodes. his strategy ensures that FL frameworks align with regulatory frameworks such as the General Data Protection Regulation (GDPR). Currently, emerging hybrid models such as hierarchical and edge-assisted FL are trying to balance global performance with privacy preservation (Zia *et al.*, 2025).

Simulation vs Real-World Deployment.

Another area of debate in Federated learning is whether simulation-based studies accurately reflect real-world ITS performance. Critics are of the opinion that simulated environments does not fully capture the dynamic nature of humans, sensor faults, and network latency (Aalavanthar *et al.*, 2025). In contrast to that opinion, other some researchers defend simulation as an essential proof-of-concept tool that allows safe, cost-effective experimentation before field deployment (Campos et al., 2024). Well-designed simulation frameworks using realistic, non-independent-and-identically-distributed (non-IID) data and client heterogeneity remain accepted in demonstrating feasibility (Chen *et al.*, 2024)

Federated Learning Efficiency Debate.

Finally, concerns about FL's efficiency continue to divide researchers. Critics highlight that large-scale vehicular networks pose challenges such as straggler effects, model aggregation bias, and communication bottlenecks (S. Zhang *et al.*, 2024)). Supporters point to advances like secure and verifiable aggregation protocols, gradient compression, and adaptive client selection as ways to mitigate computational costs and maintain scalability (S. Zhou et al., 2025; Zia et al., 2025) The present research acknowledges these efficiency challenges but confines its focus to demonstrating the feasibility of FL in ITS through simulation-based evaluation rather than cost optimisation (Campos et al., 2024).

Notification and alert mechanisms in ITS.

This section examines how timely notifications and alerts are used in intelligent mobility to improve situational awareness, reduce reaction times and prevent collisions. It summarises the technologies that deliver real-time warnings (V2V/C-V2X, dashboard and mobile notifications), highlights AI-driven alerting work, and identifies a gap: few studies integrate notification mechanisms with decentralised learning (for example federated learning) in operational ITS frameworks.

Importance of driver and commuter alerts.

Timely notifications are central to road-safety interventions because they directly affect human situational awareness and reaction latency. Alerts that convey imminent hazards whether shown on a dashboard, pushed to a driver's smartphone, or broadcast by another vehicle shorten decision loops and reduce crash risk by prompting immediate defensive actions (Albadawi et al., 2022; Cicek & Kantarci, 2023). Empirical and review studies show that well-designed alerts (clear, low false-alarm rate, context-sensitive) increase driver compliance and reduce risky behaviours in urban settings where vulnerability is high (Abdelkader et al., 2021).

Existing technologies for real-time alerts.

Three technology classes dominate current work. First, vehicle-to-vehicle and vehicle-to-infrastructure communications (V2V / V2I / C-V2X) support low-latency broadcast of Basic Safety Messages and cooperative perception information, enabling immediate warnings such as intersection collision alerts or emergency-vehicle approaches (Ficzere et al., 2023; Nagy et al., 2024). Second, in-vehicle systems (dashboard HMI, head-up displays) mediate driver alerts produced either locally (onboard sensors, DMS) or received from the network; driver-state monitoring (camera or physiological sensors) is used to trigger drowsiness and distraction alarms (Albadawi, Takruri and Awad, 2022). Third, smartphone and crowdsensing channels supply commuter-facing push notifications (vehicle arrival, incident warnings) and aggregate situational data in near real time mobile channels are especially valuable for public transport users and first-responder notifications (Cicek and Kantarci, 2023). Several studies report AI components (computer vision, anomaly detection) that automatically generate alert conditions, improving detection sensitivity while requiring careful tuning to avoid nuisance alerts (Abdelkader, Elgazzar and Khamis, 2021).

Thematic Synthesis of some related works

The application of Federated Learning (FL) in intelligent transportation systems has garnered significant research interest form notable scholars. The Table below presents a summary of some of the works.

Table 1: Comparative Analysis of Selected Related Works

No.	Authors	Relevance	Methodology	Technique(s) used	Strengths	Limitations	Knowledge contribution / Gap identified
1	(Jiang *et al.*, 2020)	Early, explicit treatment of FL for smart	Survey + conceptual analysis.	FL architectures for city sensors;	Clear mapping of FL benefits for city	High-level; lacks experimental FL for vision tasks	Shows FL suitability for urban sensing but leaves mixed-road-user

No.	Authors	Relevance	Methodology	Technique(s) used	Strengths	Limitations	Knowledge contribution / Gap identified
		city sensing shows how FL can apply to urban sensing but does not address VRUs or alerts.		privacy discussion.	sensing.	or notification integration.	perception and alert pipelines unexplored.
2	(Li *et al.*, 2020)	Foundational survey of FL challenges — useful to motivate algorithmic choices for non-IID and communication constraints.	Survey / conceptual.	Federated averaging, secure aggregation, compression.	Thorough coverage of FL problems (non-IID, privacy, communications).	Not ITS-specific; no experiments on mixed VRU detection or alerts.	Establishes core FL problems (non-IID mixed traffic, communication.
3	(R. Zhang, Wang, *et al.*, 2024)	Survey specifically on FL in ITS. Summarises applications (traffic, target recognition) and notes limitations (non-IID, device constraints).	Comprehensive survey	FL use-cases in ITS; critique of gaps.	ITS-specific synthesis; identifies research niches.	Survey limited new experiments; notes lack study on mixed VRUs and alerts.	Cites the absence of VRU-focused FL, and need for simulation work integrating alert mechanisms.
4	(Chellapandi *et al.*, 2023)	Survey on the use FL for connected & automated vehicles (CAVs). Stresses vehicle-centric focus of most FL	Systematic Survey.	FL4CAV taxonomy; privacy/security analysis.	Strong CAV focus and synthesis of FL architectures.	Highlights CAV bias and little or no attention to Vulnerable Road users, and notification systems.	Supports the claim that FL ITS literature is vehicle-biased, and that mixed-user studies are few.

No.	Authors	Relevance	Methodology	Technique(s) used	Strengths	Limitations	Knowledge contribution / Gap identified
5	(Alohali *et al.*, 2023)	FL applied to pedestrian walkway anomaly detection. one of few works using FL for pedestrian/VRU analysis (Remote Sensing).	Experimental on remote-sensing imagery with FL training.	FL + Harris Hawks Optimizer; anomaly detection pipelines.	Demonstrates FL can oversee pedestrian-oriented tasks.	Remote sensing imagery; does not integrate low-latency alerts to vehicles/commuters.	Shows FL for pedestrians is possible but lacks notification/real-time edge pipeline.
6	(Zhang *et al.*, 2022)	Lightweight vehicle–pedestrian detector designed for edge (Sensors PMC).	Experimental computer vision on traffic datasets.	YOLOv4 variants; model compression.	Demonstrates edge feasibility for VRU detection.	Focused on detection accuracy/latency; not on distributed FL or alerting.	Useful baseline for edge detectors to embed in FL clients; absence of FL+ notification integration.
7	(Ficzere *et al.*, 2023)	Survey on large-scale C-V2X / 5G deployments — pertinent for low-latency alert channels.	Systematic Survey and comparative analysis.	C-V2X, DSRC, 5G essences for ITS messaging.	Details communications stack for real-time alerts.	Focus on comms; lacks ML/FL component integration.	Identifies communication issues such as Security vulnerabilities and lack of standardised solution for end to end communication.
8	(Nagy, Török and Pethő, 2024)	Examines V2X control under unreliable networks — relevant to alert latency and robustness.	Simulation & experimental evaluation.	V2X messaging; control under packet loss.	Practical insight into network unreliability effects on safety messages.	Focused on control; not on FL or perception models.	Shows the need to model network degradation in your FL+alerts simulation.
9	(Li, Zhou and Zheng, 2024)	MDPI study on distributed learning challenges in ITS including privacy &	Conceptual + review; some experiments.	Distributed FL paradigms; privacy analyses.	ITS-focused and open access.	Survey nature; lacks VRU detection experiments and notification modules.	Justifies integrating privacy-aware FL with alert pipelines.

No.	Authors	Relevance	Methodology	Technique(s) used	Strengths	Limitations	Knowledge contribution / Gap identified
		trust — frames the design constraints.					
10	(Alqubaysi *et al.*, 2025)	Sensors paper: FL-based predictive traffic management (privacy scheme) — shows FL for traffic control but not VRU alerting.	Experimental FL system for traffic prediction; privacy scheme evaluation.	Federated traffic prediction; contained privacy-preserving measures.	Recent and ITS-applied FL demonstration.	Focus on AVs / traffic forecasting; no VRU perception or notifications.	Indicates readiness to use FL for time critical ITS tasks; notification gap remains.
11	(Aalavanthar *et al.*, 2025)	Multi-objective FL for traffic prediction — recent FL ITS experiment	FL experiments, multi-objective training, simulation.	FL aggregation strategies; traffic datasets.	Simulation oriented.	Not perception/VRU detection; no alerting.	Supports simulation-first evaluation approach; highlights lack of VRU FL studies.
12	(Barbieri *et al.*, 2022)	Demonstrates distributed FL for object classification from LiDAR/extended sensing.	Experimental with point-cloud datasets & decentralised algorithms.	Decentralised aggregation; LiDAR classification.	Demonstrates FL on perception modalities beyond images.	Vehicle/object focus. Lacks VRU classes and notification features.	Shows modality variety, but gap exists in VRU classification and notification integration.
13	(Huang *et al.*, 2024)	Responsible FL in smart transportation. Explores the use of responsible, privacy preserving, and accountable FL in ITS.	Conceptual with use-case discussion.	Responsible FL frameworks; ethics & governance.	Frames socio-technical constraints for deploying FL in ITS.	High-level; lacks technical FL and alert experimental results.	Motivates inclusion of privacy/responsibility and notification authenticity in design.

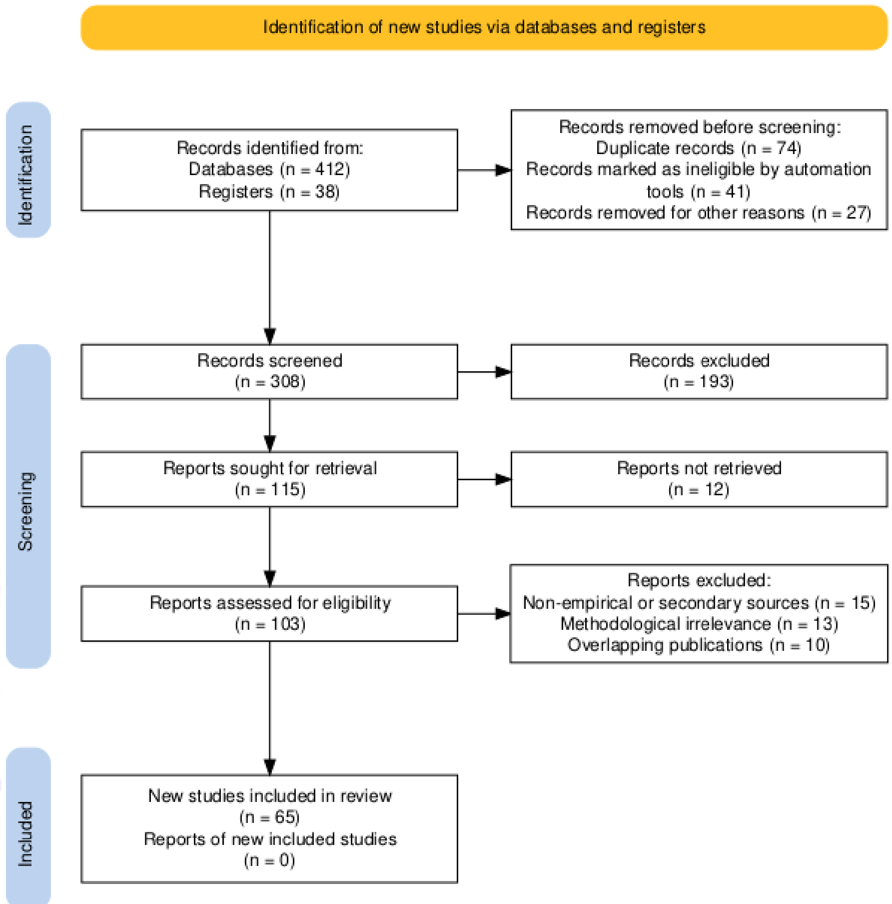
Identified Gaps from the Analysis

A review of current Federated Learning (FL) research within Intelligent Transportation Systems (ITS) reveals a heavy preoccupation with vehicle-centric applications, such as traffic forecasting or inter-vehicle perception. This focus means that vulnerable road users like pedestrians and cyclists are comparatively under-studied. Consequently, while FL is proven for traffic prediction, there is a distinct lack of studies in using it to train models that can simultaneously detect and classify a mix of different users (pedestrians, cyclists, emergency vehicles) from real-time, on-device camera streams research (Albadawi, Takruri and Awad, 2022; Cicek and Kantarci, 2023; Ficzere *et al.*, 2023). There is also a significant gap in system design, where perception and notification are treated as separate problems. Existing research are mainly divided into two main directions: one focuses on developing federated learning approaches for object detection, while the other concentrates on creating vehicle-to-everything (V2X) alert systems that operate independently of federated learning frameworks. There is a clear absence of end-to-end research that connects a privacy-preserving FL perception model directly to a secure, low-latency notification system. This gap is most critical in simulation studies. While simulations for FL networking and V2X messaging exist independently, no research was found that holistically simulates and evaluates the entire pipeline FL-based mixed-user detection plus in-simulation alert delivery, especially under realistic network degradation. This is the precise gap this proposed proof-of-concept aims to fill.

2. Methodology

This study followed a systematic literature review method to identify, evaluate, and synthesise recent research on the application of Federated Learning (FL) for detecting mixed and vulnerable road users within Intelligent Transportation Systems (ITS). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines as shown in Figure iii was carefully followed to ensure transparency and reproducibility (Haddaway *et al.,* 2022). A comprehensive search was conducted across major academic databases such as IEEE Xplore, ACM Digital Library, MDPI, ScienceDirect, and arXiv etc using Boolean combinations of keywords related to the learning method (e.g., “Federated Learning”, “Decentralised Learning”), the application domain (e.g., “Intelligent Transportation Systems”, “V2X”, “Autonomous Driving”), and the detection problem (e.g., “Pedestrian detection”, “Cyclist Detection”, “Vulnerable Road User”).

The PRISMA flow diagram as shown in Figure 3, illustrates the selection process for studies included in this review. A total of 450 records were initially identified from major databases (n = 412) and registers (n = 38). After removing duplicates (n = 74), automated exclusions (n = 41), and other irrelevant records (n = 27), 308 records were screened. Of these, 193 were excluded based on title and abstract. Full texts of 115 reports were sought, but 12 could not be retrieved. Of the 103 reports assessed for eligibility, 38 were excluded due to being non-empirical/secondary sources (n = 15), methodological irrelevance (n = 13), or overlapping publications (n = 10). Ultimately, 65 studies were included in the review for qualitative synthesis.



Only studies published between 2020, and the present were considered to capture the latest developments in this fast-evolving field. Eligible works included peer-reviewed articles, conference papers, and well-cited preprints that explicitly applied or examined Federated Learning within ITS for object or road-user detection. Non-English papers, reviews, abstracts, and studies unrelated to detection tasks were excluded. Guided by the PRISMA process identification, screening, eligibility, and inclusion data were extracted on the FL framework, ITS application area, detection models (e.g., YOLO, CNN), and addressed challenges such as data imbalance, privacy, and communication efficiency. The results were then thematically synthesised to reveal key trends, unresolved issues, and research gaps forming the analytical basis of this study.

3. Results/Analysis and Discussion

In other to outline the key trends in application focus, federated learning architectures, detection models, and evaluation metrics, a critical synthesis of the reviewed literature was done. The tabulated results highlight dominant research directions, performance patterns, and persistent gaps that define the current state of FL-based road-user detection.
Table 2 summary of Trends, Metrics, and Observations from the Reviewed Studies

Category	Focus Area	Prevalence	Key Observations
FL Application	Vehicle-Centric Applications	52%	Dominant research focus. Emphasis on traffic flow monitoring, vehicle detection, re-identification, and trajectory

Type			prediction. FL mainly used to manage large-scale, distributed vehicular data.
	Mixed Road User Detection	33%	Combines detection of vehicles and Vulnerable Road Users (VRUs), such as pedestrians and cyclists. VRU detection often secondary, indicating underrepresentation.
	VRU-Focused Applications	15%	Least studied area. Targets pedestrian/cyclist detection, tracking, and safety systems. Significant research gap exists.

Table 3 Methodological Trends in Federated Learning Architectures

Category	Architecture Type	Prevalence	Key Observations
FL Architectures	Horizontal Federated Learning (HFL)	75%	Most used. Suitable for clients sharing identical feature space but different data samples (e.g., distributed vehicle nodes, cameras). Effective in ITS scenarios.
	Vertical FL (VFL) / Federated Transfer Learning (FTL)	25%	Less common. Useful for combining heterogeneous data sources (cameras, sensors, weather inputs). Still underexplored in ITS.

Table 4 Detection Models and Performance Metrics

Category	**Model Type / Metric**	**Prevalence / Range**	**Key Observations**
Detection Models	YOLO Variants (v3, v5, v7)	**45%**	Most preferred due to high efficiency and real-time capability. Dominant for edge deployment.
	CNN/RNN Hybrid Models	**30%**	Used mainly for traffic forecasting/time-series tasks rather than object detection.
	R-CNN / Faster R-CNN	**25%**	Selected when accuracy outweighs latency concerns. Heavier models with slower inference.
Performance Accuracy	Detection Accuracy (mAP / IoU)	**78% – 92%**	FL models experience a typical accuracy drop of 2–5% compared to centralized training, especially in VRU detection tasks due to non-IID data.

Figure 5 Real-Time Constraints and Privacy Protection

Category	**Metric / Mechanism**	**Range / Usage**	**Key Observations**
Real-Time Constraints	Communication Latency (Round Time)	50 ms – >1000 ms	Lightweight models achieve sub-100 ms round times (real-time threshold). Many high-accuracy models exceed 300–1000 ms, showing conflicting definitions of “real-time” in literature.
Privacy Mechanisms	Differential Privacy (DP)	~60% usage	Widely adopted. Provides privacy but reduces model accuracy. Exhibits a clear privacy–utility trade-off.
	Homomorphic Encryption (HE)	Less common	Strong privacy but high computational overhead. Rarely used in latency sensitive ITS applications.

The synthesis revealed several notable patterns and gaps in the current use of federated learning (FL) for mixed road-user detection in intelligent transportation systems (ITS). One of the notable findings is that much of the existing work remains centred on vehicle detection, with limited attention to vulnerable road users (VRUs), even though they face greater safety risks. This imbalance points to the need for FL approaches capable of handling the variability and frequent occlusion associated with VRUs. Most studies rely on Horizontal Federated Learning (HFL), while Vertical FL and Federated Transfer Learning receive comparatively little attention, reducing the potential for combining heterogeneous data from cameras, in-vehicle sensors, weather feeds, and GPS. YOLO variants were the preferred detection models for real-time operation, yet their performance declines under non-IID conditions, indicating the need for stronger aggregation or adaptation strategies. CNN–RNN models are still used for temporal tasks, although newer transformer-based architectures remain largely unexplored. Privacy mechanisms such as differential privacy frequently reduce accuracy for minority classes, whereas homomorphic encryption remains too computationally heavy for real-time use. Variations in latency reporting further demonstrate the absence of uniform evaluation standards.

4. Conclusion

This systematic review has carefully brought together and evaluated existing research on detection systems within Intelligent Transportation Systems (ITS), with close attention to the rising shift from centralised architectures towards decentralised approaches such as Federated Learning (FL). This movement is largely motivated by the pressing demand for enhanced data confidentiality, reduced communication delay, and improved scalability particularly within complex urban environments that accommodate diverse categories of road users. It also strengthens the fact that Federated Learning offers a promising means of training effective detection models while maintaining user privacy. However, its practical adoption remains at an early stage and is hindered by recurring issues linked to variations in local data, bias during model integration, and computational efficiency. A consistent theme emerging from the literature is the evident gap in current knowledge. While FL has been successfully applied to vehicle detection and traffic forecasting, its potential for detecting and classifying mixed road users in intelligent transport system has received limited scholarly attention.

Future research should therefore concentrate on several priority areas:

i. Developing FL frameworks that are purpose-built for detecting and categorizing mixed road users, taking account of their unpredictable movements and behavioral diversity.
ii. Creating robust techniques capable of managing the non-independent and non-identically distributed (non-IID) data produced by vehicles and roadside infrastructure across varied urban contexts.
iii. Incorporating FL-based detection into real-time alert and notification systems that deliver timely warnings to both drivers and vulnerable road users; and
iv. Narrowing the divide between simulation studies and field implementation by testing FL systems in realistic, heterogeneous traffic conditions.

Addressing these research gaps will be essential for advancing the next generation of intelligent transportation systems and for realising safer, more adaptive, and more sustainable urban mobility for all categories of road users.

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