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Toward Intelligent Rural Mobility: A Systematic Review of AI-Enabled Transportation Systems and Research Gaps

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Abstract: Rural transportation systems continue to face persistent challenges associated with low population density, inadequate infrastructure, limited public transit availability, and poor digital connectivity. These limitations negatively affect accessibility, healthcare access, economic participation, and social inclusion in remote communities. Recent advancements in Artificial Intelligence (AI), Intelligent Transportation Systems (ITS), Internet of Things (IoT), and data-driven mobility services have enabled the development of intelligent and adaptive transportation solutions for low-density rural networks. This study presents a systematic review of research published between 2020 and 2026 on AI-enabled rural transportation and smart mobility systems. A PRISMA-based methodology was adopted to identify, screen, and analyze relevant studies collected from major academic databases, including IEEE Xplore, Scopus, SpringerLink, ACM Digital Library, and ScienceDirect.

Keywords: Rural mobility, Artificial Intelligence, Intelligent Transportation Systems (ITS), Smart mobility, Demand-Responsive Transit, Mobility-as-a-Service (MaaS), Transportation optimization, Accessibility.

I. INTRODUCTION

Transportation is vital for rural socio-economic development, but rural areas often lag behind cities in service quality and coverage. Low population density, long distances, and limited budgets result in infrequent or absent public transit, outdated infrastructure, and high travel costs[1]. Vulnerable groups especially low-income residents, the elderly and persons with disabilities face particular hardship; qualitative studies note “transport disadvantages” for these groups and call for a new “gold standard” of rural mobility with better infrastructure, safety, and affordability[1]. Traditional mobility solutions struggle under these conditions[2], leading governments to explore flexible alternatives.

Advancements in AI, machine learning, and connected infrastructure hold promise to modernize rural transport. Internet-of-Things (IoT) sensors and GPS tracking can create “smart land” environments to monitor and manage mobility remotely[11]. Machine learning can optimize routes and schedules, predict demand, and improve ride-sharing efficiency. For instance, optimization models have shown that demand-responsive transit (DRT) can be far more cost-efficient and lower-emission in low-demand rural areas than fixed schedules[12][5]. Moreover, intelligent mobility platforms (Mobility-as-a-Service) can integrate diverse options (buses, shuttles, bikes) to provide seamless rural transport. Emerging pilot studies explore such rural MaaS schemes, though a “knowledge gap” in dedicated rural MaaS remains[7]. This review is motivated by the need to synthesize recent research on **AI-driven smart rural mobility**, spanning AI/ML methods, IoT/ITS, shared mobility models, and inclusivity. We systematically gather literature from 2020–2026 to identify trends, gaps, and future opportunities. Our objectives are to: (1) catalog intelligent technologies and algorithms applied to rural transport; (2) analyze how smart mobility models (ride-sharing, DRT, MaaS) are adapted for villages; (3) examine inclusive design for low-connectivity and low-literacy users; and (4) outline research gaps and future directions in this interdisciplinary field.

II. SYSTEMATIC REVIEW METHODOLOGY

A. Review Framework

This study adopts a systematic literature review methodology based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to identify, evaluate, and synthesize existing research on AI-driven rural transportation systems [19]. The review focuses on intelligent mobility solutions developed for low-density and rural environments, including applications of Artificial Intelligence (AI), Machine Learning (ML), Intelligent Transportation Systems (ITS), Internet of Things (IoT), demand-responsive transportation, and smart mobility platforms [1], [3], [7].

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The review process was designed to ensure transparency, reproducibility, and methodological consistency throughout the identification, screening, eligibility assessment, and final selection of relevant studies.

B. Data Sources and Search Strategy

Relevant studies were collected from multiple academic databases, including IEEE Xplore, Scopus, SpringerLink, ACM Digital Library, ScienceDirect, and Google Scholar. The search process focused on peer-reviewed journal articles, conference papers, review studies, and transportation research published between January 2020 and March 2026.

Search queries were constructed using combinations of keywords associated with rural mobility, artificial intelligence, and smart transportation systems [2], [3], [8]. Example search strings included: (1) “Artificial Intelligence” AND “Rural Transportation”, (2) “Smart Mobility” AND “Rural Areas”, (3) “Demand-Responsive Transit” AND “Machine Learning”, (4) “Intelligent Transportation Systems” AND “Rural Mobility”, and (5) “AI-driven Transportation” AND “Smart Villages”.

C. Inclusion and Exclusion Criteria

To ensure methodological consistency and relevance, specific inclusion and exclusion criteria were applied during the screening and selection process. The review primarily focused on studies addressing rural transportation systems, intelligent mobility services, and AI-enabled transportation technologies [3], [4], [7]. Only peer-reviewed journal articles, conference papers, and review studies published between 2020 and 2026 were considered. Studies unrelated to rural mobility, non-transportation AI applications, editorials, and non-English publications were excluded from the final analysis

TABLE I
INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	Exclusion Criteria
Studies focused on rural or low-density transportation systems	Studies focused only on urban transportation systems
Research involving Artificial Intelligence (AI), Machine Learning (ML), Intelligent Transportation Systems (ITS), or Internet of Things (IoT) applications	Non-transportation AI or IoT applications
Peer-reviewed journal articles, conference papers, and review studies	Editorials, blogs, opinion articles, and unpublished reports
Publications published between 2020 and 2026	Publications published before 2020
English-language publications	Non-English publications
Studies addressing smart mobility, demand-responsive transit, ride-sharing, MaaS, or autonomous transportation in rural areas	Studies unrelated to mobility or transportation services
Research containing qualitative, quantitative, simulation-based, or experimental analysis	Studies lacking technical or methodological relevance

D. Study Selection Process

The initial database search identified approximately 2,400 records across all selected databases. Duplicate entries were removed during the preliminary screening stage, resulting in approximately 1,850 unique records. Titles and abstracts were subsequently reviewed to eliminate studies unrelated to rural transportation, intelligent mobility systems, or AI-based transportation applications.

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The overall screening and selection workflow is illustrated in Fig. 1.

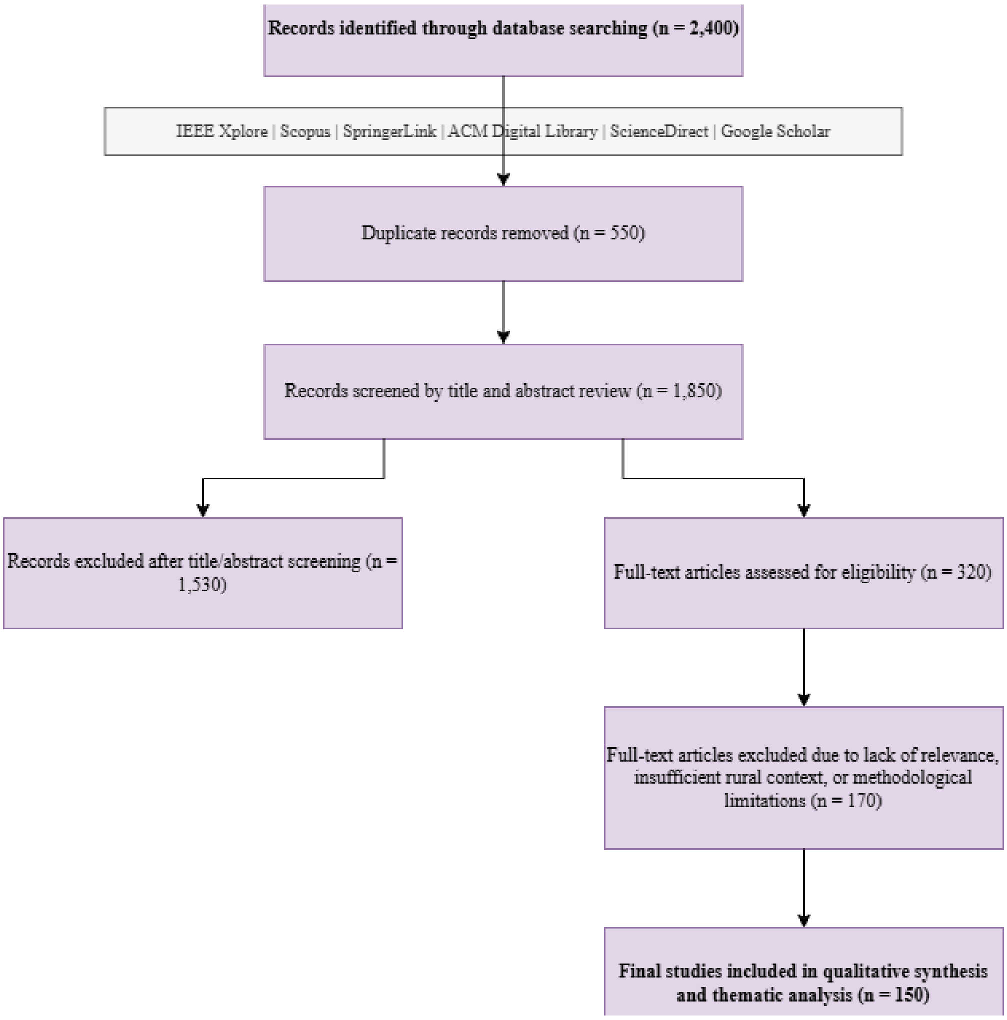

Fig. 1. PRISMA-Based Study Selection Process for AI-Driven Rural Transportation Literature Review.

E. Data Extraction and Classification

Relevant information was extracted from the selected studies, including publication year, transportation domain, AI techniques, application objectives, datasets, deployment environment, scalability considerations, and reported limitations. The extracted studies were categorized into thematic domains including AI-driven route optimization, demand-responsive transportation systems, Intelligent Transportation Systems (ITS), IoT-enabled mobility infrastructure, predictive analytics and demand forecasting, autonomous and shared mobility systems, and accessibility-oriented transportation services [5], [6], [9].

This classification enabled comparative analysis of technological trends, implementation challenges, and research gaps across different rural mobility applications.

F. Research Limitations

Several limitations should be acknowledged in this review. The study considered only English-language publications and focused primarily on peer-reviewed academic databases, which may exclude relevant industrial reports or regional studies. Additionally, the rapid evolution of AI-driven transportation technologies may lead to emerging developments beyond the selected review period. Variations in datasets, deployment environments, and evaluation metrics across studies also limited direct quantitative comparison between different rural mobility systems.

III. RURAL TRANSPORTATION CHALLENGES

Rural transport faces multifaceted challenges. Infrastructure in countryside regions is often inadequate: many roads are unpaved or poorly maintained, and transit stops are far apart[1],[14]. Low population densities lead to low transit

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ridership, making fixed-route services economically unviable[2],[10]. For example, traditional bus lines are frequently cut due to low occupancy[10], leaving "last-mile" gaps where people cannot reach major hubs. Connectivity is also limited: many rural areas lack cellular or broadband coverage, hindering real-time information delivery and telematics[15],[4]. Papastergiou et al. note that sparse infrastructure and long distances cause high signal path loss, so that wireless sensor networks in rural zones face severe coverage issues[15].

Socio-economic factors worsen the picture. Rural residents typically travel twice the distance of urbanites[16], but incomes tend to be lower, making frequent travel costly. Transport costs are disproportionately high for individuals, and taxi or rideshare services are often absent. Vulnerable groups elderly, disabled, low-income – feel these deficits acutely. Community discussions in Australia reveal a "significant gap" in mobility for these groups, who demand better integration, safety, and affordability[1],[9]. Emergency and health transport also lags: response times can be slow in remote areas, and specialized vehicles (e.g. wheelchair-accessible) are scarce.

In sum, rural areas suffer from a **connectivity divide** (limited digital/transport links) and **transport inequity** (poor service availability). These conditions underscore the need for tailored, innovative solutions (e.g., on-demand shuttle systems, multi-modal integration) rather than direct imports of urban transit models[11],[1].

IV. AI-DRIVEN SMART MOBILITY TECHNOLOGIES

Recent research applies AI and ML to improve rural transport efficiency and responsiveness. A common theme is **route and schedule optimization** for on-demand services. For instance, Martí et al. survey rural demand-responsive systems and find that AI techniques (heuristics, MILP, genetic algorithms) are primarily used to optimize vehicle routing and scheduling[3]. These models seek to minimize total travel distance or passenger wait time given scattered origins/destinations. Similarly, Molenbruch et al. formulate an integrated dial-a-ride problem (IDARP) combining bus and shuttle modes; they propose mixed-integer and large-neighborhood search (LNS) algorithms to align on-demand routes with fixed-schedule transit in rural–urban corridors[17]. In this hybrid model, three trip modes are considered (only shuttle, shuttle+bus, or walk+bus) with service quality explicitly optimized[17]. Their solution accounts for commuter patterns between villages and cities, offering an efficient schedule that synchronizes rural shuttles to town buses (the Flanders "Basic Accessibility" case)[10],[18].

Predictive analytics is another area of AI use. Demand forecasting models can predict ridership for rural routes to allocate resources. Schlenther et al. employ an agent-based simulation of a rural German region, calibrating demand from empirical data to evaluate autonomous vehicle fleets. Their model uses predicted travel patterns to determine how adding autonomous shuttles would affect existing demand e.g., expanding fleet coverage in 2023 led to better service with still lower emissions[19]. Notably, the study found that autonomous vehicles largely replaced trips on sustainable modes, suggesting effective route matching. In a different context, Maurya et al. use ML to manage **multi-connectivity** (cellular+satellite) for livestock transport in Danish rural areas: a classifier/regressor model ingests network KPIs to decide whether to switch links, maintaining robust communication where 5G is scarce[4]. This demonstrates AI's role in preserving connectivity (supporting IoT/telemetry) in rural logistics.

Ride-matching and sharing algorithms also emerge in rural studies. While large-scale ride-hailing is city-centric, smaller-scale dynamic carpool or shuttle-sharing platforms are being explored. These often use clustering and matching algorithms to pair rural riders. Research indicates, however, that innovation in AI-driven ride-sharing for rural settings is still limited. Martí et al. explicitly highlight a "lack of innovation regarding AI implementation" in rural demand-responsive systems[8], indicating an opportunity for novel ML-based matching and personalization (e.g., using generative models or reinforcement learning to optimize ride-pooling).

Finally, AI augments logistics and last-mile delivery in rural mobility. For example, crowdsourced co-modality systems integrate parcel delivery with passenger trips: a Chinese study shows buses carrying freight to countryside stops for rural deliveries[21]. While not explicitly an AI model, such systems could use optimization algorithms to route parcels via willing passengers (a form of crowdsourced sharing). More broadly, AI-driven supply chain optimization (for agri-food distribution or medical supply routes) is reported in some rural ITS literature, though scarce. Predictive maintenance of rural vehicles and infrastructure (using IoT sensor data and anomaly-detection ML) is another emerging topic for ensuring reliability, though relevant publications remain few.

In summary, current AI-driven technologies for rural mobility center on **optimization** (e.g., MILP, heuristics, agent-based models) and prediction (ML regression, neural nets) to improve efficiency[3],[12]. Studies consistently show

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benefits: e.g., replacing a rural bus with an on-demand shuttle reduced daily vehicle kilometers by ~90% and cut emissions per passenger[5]. However, many systems still rely on classic optimization rather than deep learning, reflecting the small-scale or pilot nature of most projects.

V. INTELLIGENT TRANSPORTATION SYSTEMS (ITS)

ITS and IoT technologies offer the connective fabric for smart rural mobility. **IoT-enabled vehicles** (GPS trackers, sensor-equipped vans) allow real-time fleet monitoring even in remote areas. For instance, projects like Interreg RUMOBIL compare IoT solutions for rural vs. urban planners, noting that many smart transit features (real-time information, condition monitoring) can be deployed in villages[22]. Sensors on rural buses can feed into centralized platforms, enabling adaptive dispatching. Additionally, **vehicle-to-infrastructure (V2I)** and **vehicle-to-vehicle (V2V)** communications, though more common in cities, are being adapted for rural corridors and freight routes. For example, seasonal ITS deployments (like winter weather alert systems on mountain roads) are an offshoot of urban ITS that benefit rural commuters.

A key ITS component is **real-time tracking and information systems**. Even where cellular data is patchy, some systems use hybrid connectivity to report vehicle locations. Papastergiou et al. demonstrated that machine-learning models (CNNs) can improve radio-propagation predictions for rural wireless sensor networks[15]. In practice, this means a sensor on a rural bus can more reliably send GPS updates by optimally switching between cell/satellite links (similar to the livestock use-case[4]). Meanwhile, passive ITS technologies like RFID or LoRaWAN sensors can monitor environmental conditions (road surface, weather) to inform transit planning.

Connected infrastructure also includes digital ecosystem platforms. Cloud-based mobility platforms can integrate timetable data, user apps, and vehicle telemetry. Some rural areas are experimenting with centralized mobility “hubs” or apps that aggregate options (e.g., bus schedules, ride-share posts, volunteer driver sign-ups). For example, a proposed cloud-based co-modality platform (for shared passenger-freight systems) incorporates IoT tracking of vehicles and parcels. Though urban in case, the approach shows how IoT can enable multi-modal coordination.

However, rural ITS faces connectivity limits. As noted, even IoT deployments must contend with high path loss and sparse cell towers[15]. Innovative solutions like the ML-driven cellular-satellite system ensure near-continuous links for data[4], illustrating how AI can bolster ITS. In sum, ITS technologies from GPS/GSM trackers to IoT-based scheduling lay the groundwork for smart rural transport, but must be tailored to limited infrastructure and mixed connectivity environments.

VI. SMART RURAL MOBILITY MODELS

This section reviews emerging mobility models tailored to rural contexts, often leveraging technology-enabled sharing or integration.

Demand-Responsive Transit (DRT): Instead of fixed bus lines, DRT uses flexible routes and schedules based on passenger requests. Several reviewed studies focus on the implementation of DRT systems in low-density rural areas [3], [4]. Case studies such as the Amsterdam “Mokumflex” pilot demonstrate that DRT systems can replace underutilized rural bus routes while improving operational efficiency and reducing transportation costs [4]. Existing literature categorizes DRT research into analytical optimization models and real-world pilot implementations. However, several challenges remain, including limited integration of passenger preferences, service personalization, and long-term deployment feasibility. Martí et al. emphasized the importance of user-centered mobility design to improve adoption and service accessibility in rural regions [3].

Mobility-as-a-Service (MaaS): MaaS platforms integrate multiple transportation modes within a unified digital platform for booking, route planning, and payment services. Although MaaS systems were initially developed for urban environments, recent studies have explored their adaptation for rural mobility ecosystems [7], [8]. Rural MaaS models often combine fixed-route buses, on-demand shuttles, shared mobility services, and community transportation networks. Milne et al. identified a significant research gap related to dedicated Rural Mobility-as-a-Service (RMaaS) frameworks and highlighted the need for transportation systems specifically designed for geographically dispersed communities [8]. Existing pilot studies further indicate that successful rural MaaS implementation depends not only on technological integration but also on infrastructure readiness, service flexibility, and localized transportation planning.

Ride-sharing and Crowdsourced Mobility: Shared transportation and crowdsourced mobility systems represent emerging alternatives for improving transportation accessibility in low-density environments. Several studies have investigated AI-assisted ride-sharing optimization, rural carpooling models, and app-based microtransit systems designed to reduce operational inefficiencies and transportation costs [9], [13]. Wu et al. proposed a crowdsourced co-modality transportation model in which passengers simultaneously support freight delivery services during rural transit operations [9]. Such integrated passenger-freight transportation systems demonstrate potential for improving rural logistics efficiency and transportation sustainability through coordinated mobility services and IoT-enabled tracking systems.

Community-Based Mobility Models: Community-oriented transportation solutions continue to play an essential role in rural mobility ecosystems, particularly in underserved regions where conventional transportation services remain limited. Volunteer-based transportation programs, community ride-sharing services, and locally coordinated dial-a-ride systems are frequently discussed within rural transportation policy studies [8], [14]. Technology-assisted coordination platforms, including SMS-based booking systems and low-data mobility applications, have been proposed to improve accessibility for digitally underserved populations. These models emphasize social accessibility, affordability, and transportation coverage rather than commercial optimization.

Overall, smart rural mobility systems are increasingly evolving through hybrid integration of traditional public transportation, intelligent mobility services, shared transportation models, and community-based transportation approaches [7], [8], [9]. The primary strength of these models lies in their flexibility, adaptability, and ability to address the transportation needs of geographically dispersed rural populations. Table III compares representative smart rural mobility systems discussed in the reviewed literature.

VII. ACCESSIBILITY AND INCLUSIVE TRANSPORTATION

True smart mobility systems must support accessibility and inclusivity for diverse user populations, including elderly individuals, low-literacy users, economically disadvantaged communities, and people with disabilities. Rural environments frequently experience higher levels of digital exclusion, limited transportation availability, and reduced access to mobility infrastructure [1], [8]. Consequently, several studies emphasize the importance of human-centered transportation design, multilingual interfaces, and low-connectivity accessibility solutions for rural transportation systems.

Existing literature highlights digital literacy and technological trust as major barriers to the adoption of AI-enabled rural transportation services [1], [16]. Many rural users remain unfamiliar with app-based transportation systems and may prefer alternative communication methods such as SMS notifications, voice-assisted booking systems, or offline transportation coordination platforms. As a result, researchers increasingly advocate for offline-first mobility systems capable of operating effectively in low-connectivity rural environments.

Physical accessibility also remains a critical challenge within rural transportation systems. Studies on integrated rural mobility services indicate that transportation infrastructure limitations, lack of wheelchair-accessible vehicles, inadequate pedestrian infrastructure, and absence of bicycle integration reduce transportation inclusivity [1], [8]. Milne et al. further identified concerns related to unsafe active transportation routes and limited support for multimodal mobility integration within rural public transportation systems [8].

Economic accessibility is another major consideration. Rural populations often experience transportation poverty due to limited transportation availability, high operational costs, and reduced public transit coverage [14]. Although AI-driven optimization systems can improve transportation efficiency and route planning, affordability and equitable transportation access remain strongly dependent on transportation policy frameworks, subsidy models, and infrastructure investment strategies.

Equity-oriented transportation planning also plays a significant role in the deployment of intelligent mobility systems. Several studies suggest that fully autonomous transportation systems may unintentionally favor technologically advantaged populations unless accessibility-oriented deployment strategies are incorporated during system design and implementation [5], [11]. Therefore, inclusive rural mobility requires a balanced integration of intelligent transportation technologies, low-tech accessibility alternatives, and community-centered transportation planning approaches capable of addressing the diverse mobility needs of rural populations.

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VIII. COMPARATIVE ANALYSIS

We summarize and compare representative studies and systems in Tables 1–2 below. Table 1 focuses on AI/technology-based solutions, and Table 2 on mobility models and service contexts. Each entry lists the main technologies and AI methods used, the rural context, and observed strengths/limitations.

TABLE II.
COMPARISON OF AI/ITS TECHNOLOGIES IN REPRESENTATIVE RURAL MOBILITY STUDIES (AI: ARTIFICIAL INTELLIGENCE; MOD: MOBILITY-ON-DEMAND GA: GENETIC ALGORITHM; MILP: MIXED-INTEGER LINEAR PROGRAMMING; MV: MODEL).

Study	Technology	Contribution	Limitation
Martí et al. (2023)	Optimization Algorithms	Improved rural route scheduling	Limited real-time adaptability
Schlenther et al. (2025)	Agent-Based Simulation	Autonomous rural mobility evaluation	Simulation-only validation
Maurya et al. (2026)	ML Connectivity Models	Enhanced rural transport connectivity	Infrastructure dependency
Coutinho et al. (2020)	DRT Optimization	Reduced cost and emissions	Limited coverage in sparse regions

TABLE III.
COMPARISON OF SMART MOBILITY MODELS AND SERVICES IN RURAL CONTEXTS.

Mobility Model	Key Advantage	Major Challenge	Rural Suitability
Demand-Responsive Transit (DRT)	Flexible routing and reduced operational cost	Requires accurate demand prediction	High
Mobility-as-a-Service (MaaS)	Integrated multimodal transportation access	Dependence on digital infrastructure	Moderate
Ride-Sharing Platforms	Improved vehicle utilization efficiency	Low adoption in sparsely populated regions	Moderate
Autonomous Rural Transit	Reduced dependency on human drivers	High infrastructure and regulatory requirements	Low–Moderate
Passenger–Freight Integration	Enhanced transportation efficiency and sustainability	Coordination and scheduling complexity	High

These comparisons illustrate diverse approaches: AI-driven algorithms (Table II) versus service frameworks and empirical case studies (Table III). Strengths like emission reduction[5] and tailorability are contrasted with limitations such as limited deployment scale and user adoption concerns.

The comparison of smart rural mobility models indicates that demand-responsive transportation systems are currently the most feasible and adaptable solution for low-density rural environments. These systems provide operational flexibility and improved service efficiency while addressing the limitations of traditional fixed-route public transportation models. Mobility-as-a-Service platforms and ride-sharing systems demonstrate significant potential for improving transportation accessibility; however, their effectiveness remains dependent on digital connectivity, smartphone accessibility, and user adoption rates within rural communities. Autonomous rural transit systems continue to face substantial infrastructural, regulatory, and economic barriers despite promising developments in intelligent navigation technologies.

Passenger–freight integration models have emerged as a sustainable transportation approach capable of improving resource utilization and reducing operational costs in geographically dispersed regions. Nevertheless, effective

coordination between passenger services and logistics operations remains a significant implementation challenge across existing rural mobility frameworks.

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IX. AI-DRIVEN RURAL MOBILITY TAXONOMY FRAMEWORK

The rapid growth of intelligent transportation technologies has resulted in diverse approaches toward rural mobility optimization. However, existing studies often focus on isolated technological implementations without presenting a unified analytical structure for AI-enabled rural transportation systems. To address this limitation, this review proposes a multi-layered taxonomy framework that categorizes AI-driven rural mobility systems based on infrastructure, intelligence mechanisms, mobility services, and user-centric accessibility components.

The proposed framework organizes the rural smart mobility ecosystem into four interconnected layers. The first layer consists of infrastructure components, including IoT devices, GPS systems, wireless sensor networks, cloud platforms, and edge-computing architectures responsible for data acquisition and connectivity. The second layer represents intelligent processing mechanisms, including Machine Learning (ML), predictive analytics, optimization algorithms, reinforcement learning, and data-driven decision systems used for transportation planning and operational management. The third layer focuses on mobility service models, including demand-responsive transportation systems, Mobility-as-a-Service (MaaS), ride-sharing platforms, autonomous rural transit, and integrated passenger-freight transportation systems. These services utilize intelligent decision-making models to improve transportation efficiency, route flexibility, and resource utilization in low-density environments.

The fourth layer emphasizes user-centric and accessibility-oriented components. This includes inclusive transportation interfaces, low-literacy mobility applications, multilingual systems, offline-first communication frameworks, and affordable mobility services designed for elderly populations, economically disadvantaged users, and digitally underserved rural communities.

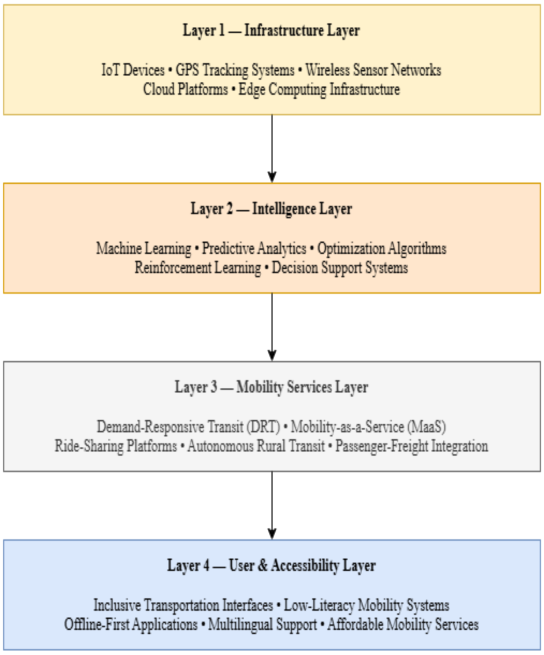

Fig. 2. Multi-Layer Taxonomy Framework for AI-Driven Rural Mobility Systems.

X. QUANTITATIVE RESEARCH TREND ANALYSIS

To examine the evolution of research related to AI-driven rural transportation systems, a quantitative analysis of the selected literature was performed based on publication year, dominant technological approaches, transportation models, and thematic research domains. The analysis demonstrates a significant increase in research activity after 2021, primarily driven by advancements in Artificial Intelligence (AI), Intelligent Transportation Systems (ITS), Internet of Things (IoT), and smart mobility infrastructure.

The publication trend analysis indicates that demand-responsive transportation systems, predictive analytics, and intelligent route optimization remain the most extensively studied domains within rural smart mobility research.

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Additionally, recent studies increasingly emphasize sustainable transportation, autonomous rural mobility, edge computing, and data-driven transportation planning.

The analysis further reveals that optimization algorithms, machine learning models, and simulation-based mobility systems are more commonly adopted than deep learning or fully autonomous transportation frameworks. This trend reflects the infrastructural and computational limitations commonly associated with rural deployment environments. Furthermore, studies focusing on accessibility, inclusivity, and low-connectivity transportation systems remain comparatively limited despite their importance for underserved rural communities.

A quantitative analysis of the selected literature was conducted to identify publication trends and dominant research themes in AI-driven rural transportation systems. The year-wise distribution of selected studies is presented in Table IV.

TABLE IV
YEAR-WISE DISTRIBUTION OF SELECTED STUDIES

Publication Year	Number of Studies
2020	12
2021	18
2022	24
2023	31
2024	37
2025	20
2026	8

The analysis indicates a gradual increase in research publications after 2021, reflecting growing academic and industrial interest in intelligent rural mobility systems, demand-responsive transportation, and AI-enabled transportation infrastructure.
The reviewed studies were further categorized into major thematic domains based on transportation application areas and AI-driven mobility objectives. The distribution of dominant research domains is presented in Table V.

TABLE V
DISTRIBUTION OF MAJOR RESEARCH DOMAINS

Research Domain	Percentage (%)
Demand-Responsive Transportation	28%
Route Optimization and Scheduling	22%
Intelligent Transportation Systems (ITS)	18%
IoT and Smart Infrastructure	14%
Predictive Analytics and Forecasting	10%
Autonomous Rural Mobility	5%
Accessibility and Inclusive Transportation	3%

The findings indicate that demand-responsive transportation systems and Intelligent Transportation Systems (ITS) remain the most extensively studied areas within AI-driven rural mobility research. In contrast, accessibility-oriented mobility systems and autonomous rural transportation continue to receive comparatively limited research attention.

XI. RESEARCH TREND ANALYSIS DISCUSSION

The quantitative analysis demonstrates a continuous increase in research interest in AI-driven rural transportation systems over recent years. The highest concentration of publications was observed between 2023 and 2025, indicating growing academic and industrial attention toward intelligent rural mobility solutions and sustainable transportation systems.

Thematic analysis further shows that demand-responsive transportation and route optimization remain dominant research areas due to their practical applicability and lower infrastructural requirements. In contrast, accessibility-focused mobility systems and autonomous rural transportation remain relatively underexplored despite their long-term significance for inclusive and sustainable rural mobility ecosystems.

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The findings also indicate that most current research emphasizes algorithmic optimization and simulation-based evaluation rather than large-scale real-world deployment. This highlights the need for future studies involving field implementation, infrastructure-aware AI systems, and low-connectivity transportation frameworks suitable for geographically dispersed rural regions.

XII. RESEARCH GAPS AND CHALLENGES

Despite significant advancements in AI-driven rural transportation research, several technological, infrastructural, and implementation-related challenges remain unresolved. Existing intelligent mobility solutions are often designed using urban-centric transportation datasets and infrastructure assumptions, limiting their adaptability to geographically dispersed and low-density rural environments. Consequently, many AI-based transportation models demonstrate reduced performance when applied to regions with inconsistent connectivity, limited digital infrastructure, and sparse transportation demand patterns.

One of the major research gaps identified in the reviewed literature is the limited availability of rural transportation datasets. Most machine learning and predictive mobility systems rely heavily on historical transportation data, real-time traffic information, and continuous connectivity infrastructure. However, rural regions frequently lack reliable transportation datasets, sensor coverage, and intelligent monitoring infrastructure, restricting the effectiveness of data-driven mobility optimization systems.

Another significant challenge involves scalability and deployment feasibility. While several studies report promising results using simulation-based transportation models, large-scale real-world deployment remains limited. Intelligent transportation systems in rural environments must address issues related to operational cost, infrastructure dependency, maintenance complexity, and long-term sustainability. Additionally, transportation systems designed for densely populated urban environments are often economically unsuitable for low-demand rural regions.

Accessibility and inclusivity also remain underrepresented within current rural mobility research. Existing transportation platforms frequently assume smartphone accessibility, digital literacy, and stable internet connectivity. These assumptions may exclude elderly populations, economically disadvantaged communities, and digitally underserved users from accessing intelligent mobility services. Furthermore, multilingual transportation interfaces and offline-first mobility applications remain insufficiently explored within existing literature.

The analysis further reveals limited research involving edge AI, decentralized transportation intelligence, low-connectivity mobility systems, and energy-efficient transportation architectures for rural deployment environments. Ethical concerns related to transportation data privacy, algorithmic transparency, surveillance risks, and equitable transportation access also require greater academic attention within future intelligent mobility research.

TABLE VI
MAJOR RESEARCH GAPS IN AI-DRIVEN RURAL MOBILITY SYSTEMS

Research Area	Identified Gap	Research Need
Transportation Datasets	Limited rural mobility datasets	Development of region-specific open datasets
Connectivity Infrastructure	Dependence on stable internet access	Offline-first and low-connectivity systems
AI Deployment	Lack of real-world implementation	Large-scale field deployment studies
Accessibility	Limited support for digitally underserved users	Inclusive and multilingual mobility platforms
Autonomous Mobility	Limited rural autonomous transit research	Infrastructure-aware autonomous systems
Sustainability	High infrastructure and operational costs	Energy-efficient transportation frameworks
Data Privacy	Insufficient focus on ethical AI governance	Privacy-aware mobility architectures

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The identified research gaps indicate that current AI-driven rural transportation research remains heavily focused on algorithmic optimization rather than infrastructure-aware deployment and inclusive transportation accessibility. Existing intelligent mobility systems frequently overlook the socioeconomic and connectivity constraints present within geographically dispersed rural communities. Addressing these limitations will require interdisciplinary collaboration involving transportation engineering, artificial intelligence, communication systems, and public policy to develop scalable, affordable, and inclusive rural mobility ecosystems.

XIII. FUTURE RESEARCH DIRECTIONS

Future research in AI-driven rural transportation systems is expected to focus on intelligent, adaptive, and infrastructure-aware mobility solutions capable of operating efficiently within low-density and resource-constrained environments. Emerging developments in edge computing, federated learning, autonomous mobility systems, and generative artificial intelligence are likely to significantly influence the evolution of intelligent rural transportation ecosystems.

One promising direction involves the integration of edge AI and decentralized transportation intelligence for low-connectivity rural environments. Edge-based transportation systems can reduce dependency on centralized cloud infrastructure by enabling localized decision-making, real-time route adaptation, and distributed mobility optimization. Such approaches may improve transportation reliability in remote regions with unstable internet connectivity.

Another important research direction concerns autonomous and semi-autonomous rural transportation systems. Future intelligent mobility platforms are expected to incorporate AI-assisted navigation, adaptive vehicle coordination, and autonomous fleet management to improve transportation accessibility in geographically isolated communities. However, infrastructure readiness, safety regulations, and economic feasibility remain critical challenges for large-scale deployment.

Generative AI and large language model-based mobility assistants also present emerging opportunities for intelligent transportation accessibility. AI-driven conversational transportation systems may support multilingual communication, low-literacy mobility assistance, and personalized route planning for elderly and digitally underserved populations. Additionally, future transportation systems are expected to emphasize sustainability through energy-efficient routing, electric rural transit integration, and environmentally adaptive transportation planning.

Future studies should also prioritize real-world pilot implementations, interdisciplinary collaboration, ethical AI governance, and region-specific transportation frameworks tailored to diverse rural environments. Developing scalable, inclusive, and sustainable mobility ecosystems will be essential for bridging transportation inequality and improving quality of life within underserved rural communities.

XIV. CONCLUSION

Rural transportation systems continue to experience substantial challenges related to accessibility, infrastructure limitations, economic feasibility, and transportation service availability. The emergence of Artificial Intelligence (AI), Intelligent Transportation Systems (ITS), Internet of Things (IoT), and data-driven mobility platforms has created new opportunities for improving transportation efficiency, connectivity, and inclusivity within geographically dispersed rural environments. This study presented a systematic review of AI-driven rural transportation research published between 2020 and 2026, focusing on intelligent mobility technologies, transportation optimization approaches, and emerging smart mobility frameworks designed for low-density regions.

The review identified demand-responsive transportation systems, intelligent route optimization, predictive analytics, IoT-enabled infrastructure, and integrated mobility services as the dominant research directions within current rural mobility literature. The findings indicate that AI-based transportation systems can significantly improve operational efficiency, route flexibility, transportation accessibility, and environmental sustainability when compared with traditional fixed-route transportation models. Additionally, recent developments in edge computing, autonomous mobility systems, and intelligent transportation coordination demonstrate strong potential for enhancing rural mobility ecosystems in the coming years.

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Despite these advancements, the analysis revealed several unresolved research and deployment challenges. Existing intelligent transportation systems frequently depend on stable digital infrastructure, region-specific datasets, and high levels of technological accessibility, limiting their applicability in underserved rural communities. Scalability constraints, limited real-world deployment, affordability concerns, and insufficient focus on accessibility-oriented mobility design remain significant barriers to large-scale implementation. Furthermore, ethical concerns related to transportation data governance, algorithmic transparency, and equitable transportation access require greater consideration within future rural mobility research.

This review contributes a structured analytical perspective on AI-driven rural transportation systems through the development of a multi-layer taxonomy framework, comparative mobility analysis, and quantitative research trend evaluation. The proposed framework highlights the interrelationship between intelligent infrastructure, AI-based decision systems, mobility service models, and accessibility-oriented transportation design within rural smart mobility ecosystems.

Future intelligent rural transportation systems are expected to increasingly integrate edge AI, decentralized mobility intelligence, autonomous transportation coordination, and generative AI-assisted accessibility services. However, the long-term success of these systems will depend on the development of scalable, affordable, inclusive, and infrastructure-aware transportation architectures tailored specifically to the socioeconomic and geographical characteristics of rural communities. Continued interdisciplinary collaboration among researchers, policymakers, transportation planners, and technology developers will be essential for creating sustainable intelligent mobility ecosystems capable of reducing transportation inequality and improving quality of life in underserved rural regions.

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