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ARTIFICIAL INTELLIGENCE APPLICATIONS FOR ENHANCING SAFETY IN P-HAILING SERVICES: A SYSTEMATIC LITERATURE REVIEW

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Abstract:

The rapid growth of p-hailing services has transformed urban transportation and last-mile delivery operations, created new economic opportunities while simultaneously raising concerns regarding rider safety, traffic risks, and operational sustainability. As p-hailing riders are frequently exposed to road hazards, demanding work conditions, and dynamic traffic environments, there is an increasing need to explore how artificial intelligence (AI) can enhance safety within this sector. However, existing studies on AI applications in transportation safety remain fragmented across different disciplines and technological domains, limiting a comprehensive understanding of their contributions to p-hailing safety. Therefore, this study aims to systematically review the current literature on AI applications for enhancing safety in p-hailing services. A Systematic Literature Review (SLR) approach was adopted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Advanced search strategies were conducted in the Scopus and Web of Science (WoS) databases using combinations of keywords related to "gig economy", "p-hailing", "safety", and "artificial intelligence". The review focused on peer-reviewed journal articles published between 2020 and 2026. Following the identification, screening, eligibility, and inclusion processes, a total of 45 articles were selected as the final dataset for analysis. The findings revealed four major themes: (1) AI-Driven Road Safety, Driver Behaviour, and Human Risk Detection; (2) AI, Machine Learning, and Digital Technologies for Transport Infrastructure Resilience; (3) Intelligent Transport Systems, Traffic Estimation, and Mobility

Simulation; and (4) Shared Mobility, Equity, Sustainability, and Transport Governance. The review highlights that AI technologies are increasingly employed to support risk detection, behavioural monitoring, predictive safety assessment, traffic management, infrastructure resilience, and sustainable mobility governance. Overall, the findings demonstrate the significant potential of AI to improve safety outcomes in p-hailing services while identifying important research directions for policymakers, platform operators, and future researchers seeking to develop safer and more resilient mobility ecosystems.

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Keyword:

AI, Gig Economy, P-Hailing, Safety

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Introduction

Artificial Intelligence (AI) has emerged as a transformative force across various industries, offering innovative solutions to enhance safety, efficiency, and operational reliability. In the context of P-hailing services platform-based delivery systems that rely on motorcycles or similar vehicles AI applications hold immense potential to address critical safety challenges. These services, characterized by high-speed operations in dense urban environments, face risks such as traffic accidents, rider fatigue, and unpredictable road conditions. Leveraging AI technologies, such as machine learning, computer vision, and predictive analytics, can enable real-time monitoring, risk assessment, and proactive safety interventions. For instance, AI-powered systems can analyze rider behavior, detect unsafe driving patterns, and provide timely alerts to prevent accidents (Kinowska & Sienkiewicz, 2022; Meijerink & Bondarouk, 2023). Additionally, predictive maintenance algorithms can ensure vehicle reliability, reducing the likelihood of mechanical failures during operations (Lakshmi et al., 2024).

The integration of AI into P-hailing services not only enhances safety but also contributes to broader goals of sustainable and efficient urban mobility. By analyzing vast amounts of data, AI systems can optimize delivery routes, reduce fuel consumption, and minimize environmental impact (Lakshmi et al., 2024; Dawson et al., 2024). Furthermore, wearable AI devices and computer vision technologies can monitor rider health and environmental conditions, ensuring compliance with safety protocols and mitigating occupational hazards (Kinowska & Sienkiewicz, 2022; Liu et al., 2024). Despite these advancements, challenges such as data quality, algorithmic bias, and the need for explainable AI systems remain significant barriers to widespread adoption (Cebulla et al., 2023). Addressing these issues through robust regulatory frameworks and innovative research will be crucial for realizing the

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full potential of AI in enhancing safety within P-hailing services. This exploration underscores the transformative role of AI in creating safer, more efficient, and sustainable delivery ecosystems.

Literature Review

Artificial intelligence is increasingly used to enhance safety in p-hailing and ride-hailing services by addressing both road-risk and platform-risk problems. The literature clusters around five applications: demand and dispatch intelligence, driver state monitoring, passenger protection through risk prediction, privacy-preserving safety monitoring, and cyber-secure platform governance (Megat Ali et al., 2024; Won et al., 2023; Cohen et al., 2023). Ride-hailing platforms generate large volumes of location, order, and trajectory data, which machine learning can use to improve matching, routing, and operational control (Megat Ali et al., 2024). Although these operational studies are often framed around efficiency, they also matter for safety because better allocation, shorter waiting times, and more reliable routing can reduce rider exposure during pickup and travel, especially in uncertain urban contexts (Megat Ali et al., 2024; Won et al., 2023). Recent reviews also place trust, security, and the latency–security trade-off alongside forecasting and matching as core ride-hailing research areas, showing that safety is now treated as a system-design objective rather than a narrow emergency-response feature (Beguni et al., 2026).

A major strand of the literature targets driver-related crash risk through AI-based fatigue, drowsiness, and distraction detection. Reviews consistently identify four signal families—image or video analysis, biological signals, vehicle movement analysis, and hybrid methods—and show that computer vision can infer sleepiness from eye closure, yawning, head movement, and related behavioural cues (Duke, 2022). Applied studies report high performance for real-time monitoring systems, including 99.8% anomaly detection in a CNN-based behavioural system, 99.2% training accuracy with 97.54% sensitivity in a head-posture BiLSTM model, 96.54% testing accuracy in camera-based yawning and eye-state detection, and 94% accuracy in a cyber-physical driver behaviour model (Anning-Dorson, 2025; Hilstob & Massie, 2022). Broader driver-monitoring surveys further show that AI can detect unusual, distracted, drunk, or reckless driving, classify common driver activities with 91.4% accuracy, and support real-time warnings, making in-vehicle monitoring one of the most mature safety applications relevant to p-hailing (Megat Ali et al., 2024).

Another strand shifts from crash prevention to passenger security. Empirical ride-hailing research shows that users value driver and vehicle identification, as well as real-time trackability and traceability, because these features strengthen trust and reduce perceived danger before and during trips (Zhang et al., 2022). At the same time, passengers report distrust in platform safeguards, exposure to malicious or criminal activity, reckless driving, smartphone distraction by drivers, and fare disputes that can escalate into conflict (Zhang et al., 2022). To move from reactive support to prevention, recent work uses large-scale car-hailing order data to estimate urban block-level area risk, detect risky behaviour through fraud trajectory recognition and fraud pattern mining, and jointly model the link between risky areas and risky behaviours for early warning (Donoghue, 2025). Related crime-prediction studies in transportation and urban safety also show that neural networks, GIS-based spatial analysis, and transformer time-series models can forecast high-crime transport areas and fraud trends, supporting more proactive safety management (Donoghue, 2025).

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Computer vision is also being extended to detect abnormal events affecting passengers directly. Deep-learning surveillance systems in autonomous shuttle and public transport settings can identify aggression, bag-snatching, vandalism, accidents, and unsafe behaviours in real time, with support for embedded deployment and multiple learning paradigms when labelled data are scarce (Chou & Gomes, 2023). In a deployed public-transport violence-detection pipeline, validation accuracy rose from 93% to 97% after including simulated live data, and field testing still exposed false negatives during rainy weather, underscoring both the promise of real-time AI monitoring and the importance of robustness under changing environmental conditions (Bates et al., 2023). Similar route-safety work now combines crime, environmental, demographic, and real-time contextual signals to rank safer corridors, suggesting that future p-hailing apps could recommend not just faster routes but safer ones (Thilagavathi & Subashini, 2025).

The literature also shows that safety and privacy are tightly coupled in p-hailing systems. Riders must disclose location data for matching and trajectory monitoring, creating risks of privacy leakage, profiling, inference attacks, and broader cyber threats across AI-enabled mobility platforms (Baltador et al., 2025; Gu, 2024; Gonzalez-Cabello et al., 2025). Privacy-preserving designs therefore represent a distinct AI safety application: pRide uses deep learning demand prediction while protecting ride matching, and pSafety uses homomorphic-encryption-based trajectory similarity methods to detect route deviation without revealing user locations (Baltador et al., 2025; Gu, 2024).

The main conclusion is that AI can substantially enhance safety in p-hailing services, but the strongest literature treats safety as a multi-layer problem spanning driver behavior, passenger protection, route and crime prediction, privacy preservation, and cybersecurity governance rather than any single detection model (Gonzalez-Cabello et al., 2025).

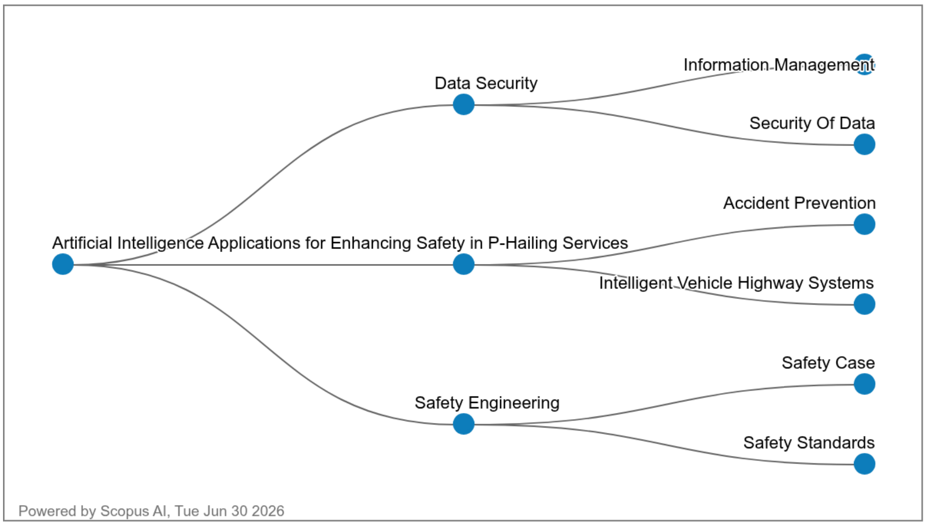

Figure 1: Conceptual Map of Bibliography of Scopus

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Material and Methods

Identification

This study adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a transparent and systematic literature review process. The review commenced with the identification stage, during which relevant publications were retrieved from two major academic databases, namely Scopus and Web of Science (WoS). These databases were selected due to their extensive coverage of high-quality, peer-reviewed literature across various disciplines. The search process resulted in 464 records from Scopus and 80 records from WoS, yielding a total of 544 publications for further screening and assessment.

To ensure comprehensive coverage of the literature, a set of keywords related to the study topic was developed. The primary keyword used was "p-hailing rider", which refers to individuals engaged in platform-based delivery services through digital applications. As the terminology used in previous studies varies across countries and contexts, additional related terms such as "gig worker", "gig economy worker", "platform worker", "delivery rider", "courier rider", "food delivery rider", and "last-mile delivery worker" were also considered. These keywords were identified through an examination of previous studies, dictionaries, thesauri, and subject-specific literature to capture a broader range of relevant publications.

The identified keywords were then combined using Boolean operators (AND, OR) to construct appropriate search strings for both databases. The use of multiple synonymous terms helped to minimise the risk of excluding relevant studies due to differences in terminology. This strategy enabled the retrieval of literature related to p-hailing riders and their working conditions, ensuring that the review captured a comprehensive body of evidence relevant to the research objectives.

Table 1: The Search String

Database	Search String
Scopus	TITLE-ABS-KEY (("artificial intelligence" OR AI OR "machine learning" OR "deep learning" OR "neural network*") AND (safety OR "safety enhancement" OR "risk reduction" OR "safety improvement") AND ("P-Hailing" OR "ride-hailing" OR "ride sharing" OR "transportation network" OR "mobility service")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (SUBJAREA , "SOCI")) AND PUBYEAR > 2019 AND PUBYEAR < 2027 Date of Access: July 2026
WoS	(("artificial intelligence" OR AI OR "machine learning" OR "deep learning" OR "neural network*") AND (safety OR "safety enhancement" OR "risk reduction" OR "safety improvement") AND ("P-Hailing" OR "ride-hailing" OR "ride sharing" OR "transportation network" OR "mobility service")) (Topic) and 2026 or 2025 or 2024 or 2023 or 2022 or 2020 or 2021 (Publication Years) and Article (Document Types) and English (Languages) Date of Access: July 2026

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Screening

During the screening stage, all records identified from Scopus and Web of Science were evaluated to determine their relevance to the research objectives. Duplicate records retrieved from both databases were first identified and removed to ensure that each study was only considered once. Subsequently, the remaining publications were screened based on their titles, abstracts, and keywords to assess their relevance to the topic of p-hailing riders and the selected area of investigation.

To ensure consistency and quality in the selection process, predefined inclusion and exclusion criteria were established, as presented in Table 2. Only studies published in English were considered, while publications in other languages were excluded. The review was limited to studies published between 2020 and 2026 to capture the most recent developments and evidence related to p-hailing riders. In addition, only journal articles at the final publication stage were included, whereas conference papers, books, book chapters, review articles, and articles published as "in press" were excluded from the review.

The application of these criteria enabled the researchers to systematically narrow down the initial pool of publications to those most relevant to the study. Studies that did not meet the language, publication year, document type, or publication stage requirements were removed from further consideration. The remaining articles were then subjected to the eligibility assessment stage to determine their suitability for inclusion in the final systematic literature review.

Table 2: The Selection Criterion in Searching

Criterion	Inclusion	Exclusion
Language	English	Non-English
Time line	2020 – 2026	< 2020
Literature type	Journal (Article)	Conference, Book, Review
Publication Stage	Final	In Press

Eligibility

The third stage of the PRISMA process involved the eligibility assessment. At this stage, 178 articles were retained and subjected to a more detailed review. The full texts, titles, abstracts, and key contents of the articles were carefully examined to determine their suitability and relevance to the research objectives. This process ensured that only studies directly related to the topic under investigation were considered for inclusion in the final review.

During the eligibility assessment, 133 articles were excluded for several reasons. Some studies were found to be outside the scope of the research area, while others had titles that were not sufficiently relevant to the study topic. Additional articles were excluded because their abstracts did not address the research objectives or because the full text could not be accessed for comprehensive evaluation. These exclusion criteria helped maintain the quality and relevance of the selected literature.

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Following the eligibility screening, 45 studies met all inclusion criteria and were retained for the qualitative analysis stage. These articles formed the final dataset for the systematic literature review and were subsequently analysed to identify key themes, findings, trends, and research gaps related to p-hailing riders and the focus area of this study.

Data Abstraction and Analysis

This study employed an integrative review approach to systematically analyse and synthesise findings from qualitative studies related to safety in p-hailing services. An integrative review enables researchers to combine evidence from multiple empirical studies, thereby providing a comprehensive understanding of a research domain and facilitating the identification of emerging patterns, themes, and knowledge gaps. The approach was selected because it allows for the inclusion of studies with diverse methodologies while maintaining a rigorous and structured review process.

The thematic development process began with an in-depth examination of the 45 selected articles included in the qualitative synthesis. Each article was carefully reviewed to extract relevant information regarding research objectives, methodological approaches, key variables, and principal findings associated with safety in p-hailing services. The extracted data were subsequently organised and compared to identify recurring concepts and significant areas of investigation. Particular attention was given to the relationships among the identified factors, research trends, and the empirical evidence reported across studies.

Following the data extraction process, the researchers collaboratively analysed and categorised the findings into meaningful themes and sub-themes. Throughout the analysis, detailed records were maintained to document interpretations, emerging insights, analytical decisions, and potential areas of uncertainty. This audit trail enhanced the transparency and dependability of the review process. To strengthen the credibility of the thematic structure, the identified themes were continuously reviewed and compared across studies. Any discrepancies or differences in interpretation were discussed among the researchers until a consensus was achieved, ensuring that the final themes accurately reflected the evidence presented in the selected literature.

The author and co-author review phase helped ensure each sub-theme's clarity, importance, and adequacy by establishing domain validity. Adjustments based on the discretion of the author based on feedback and comments by experts have been made. The questions are as follows below:

RQ1. How are artificial intelligence technologies applied to enhance road safety through driver behaviour monitoring and human risk detection in transportation and p-hailing environments?
RQ2. How do artificial intelligence, machine learning, and digital technologies contribute to improving the resilience and safety of transportation infrastructure and networks?
RQ3. How are artificial intelligence and intelligent transport technologies utilized to support traffic estimation, mobility simulation, and transportation safety management?
RQ4. How do artificial intelligence-enabled mobility systems influence safety, sustainability, equity, and governance within shared mobility and p-hailing services?

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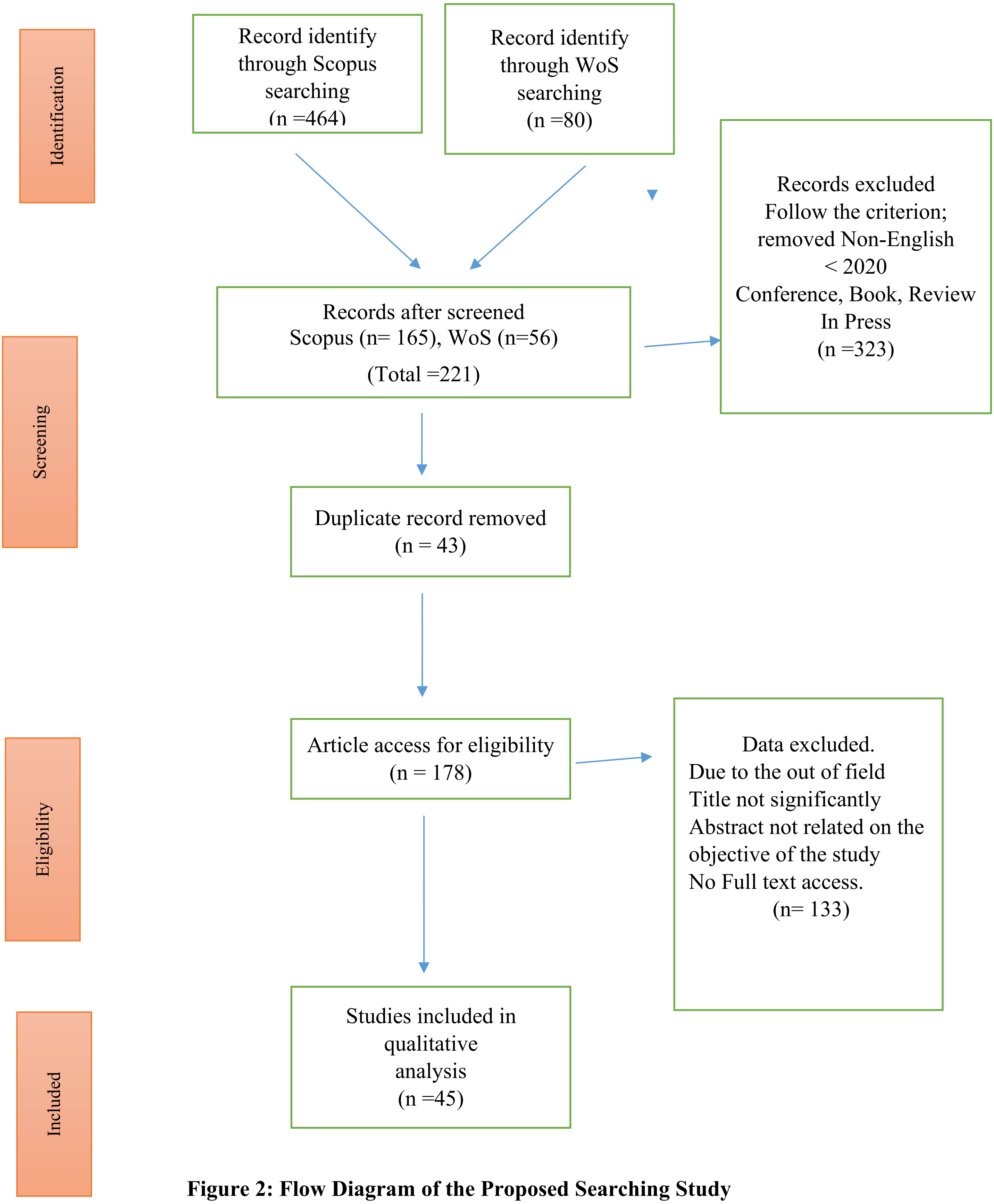

Figure 2: Flow Diagram of the Proposed Searching Study

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Result and Discussion

AI-Driven Road Safety, Driver Behaviour, and Human Risk Detection

The theme of AI-driven road safety, driver behaviour, and human risk detection shows that artificial intelligence is increasingly used to identify safety risks before road incidents occur. Zhang et al. (2026) focus on driving visibility by using point cloud data to evaluate urban road safety, showing that environmental visibility can be measured more objectively through data-based indicators. This is important because limited visibility may affect driver judgement, reaction time, and overall road awareness. Fu et al. (2026) extend this concern by examining driver fatigue detection through a multimodal few-shot learning model, suggesting that artificial intelligence can support early identification of tired or less alert drivers even when available training data are limited. Ghoreishi et al. (2025) also link artificial intelligence with human-related safety risk by using deep learning to classify drivers with mild cognitive impairment, which indicates that road safety is not only affected by road conditions but also by the physical and cognitive condition of drivers. Sadat and Raihan (2026) provide a behavioural angle by comparing riding behaviour, speeding, and law adherence between professional and nonprofessional riders. Together, these studies indicate that road safety is shaped by a combination of environmental visibility, driver alertness, cognitive ability, and behavioural compliance. Within p-hailing services, such findings are relevant because riders operate in complex urban environments, often under time pressure, exposure to traffic risks, and platform-based delivery demands.

The findings across these studies suggest that artificial intelligence can improve safety analysis by converting complex road and human behaviour data into measurable risk indicators. Zhang et al. (2026) demonstrate that point cloud data can support a more detailed understanding of urban road visibility, which may help identify unsafe road segments or areas with poor visual conditions. Fu et al. (2026) contribute to the same safety direction by showing that driver fatigue can be detected through a dual-stream multimodal model, where different data inputs are combined to improve recognition accuracy. Ghoreishi et al. (2025) further show that deep learning can be applied to classify driver conditions related to mild cognitive impairment, making it possible to detect hidden human factors that may not be visible through ordinary observation. Sadat and Raihan (2026) add that professional and nonprofessional riders may show different patterns in speeding, riding behaviour, and law adherence, which is particularly important for p-hailing because many riders are expected to complete tasks quickly while still following road rules. When combined, these studies show that AI-based safety systems are useful not only for detecting road hazards but also for understanding how drivers and riders behave in real traffic situations. The discussion suggests that safety improvement should not rely only on enforcement or training, but also on data-driven monitoring, predictive detection, and better understanding of risky behaviour patterns.

Overall, this theme highlights that AI applications can strengthen safety in p-hailing services through three main contributions: environmental risk assessment, human condition detection, and behavioural risk evaluation. Zhang et al. (2026) show the value of measuring road visibility using point cloud data, while Fu et al. (2026) and Ghoreishi et al. (2025) focus on detecting internal driver-related risks such as fatigue and cognitive impairment. Sadat and Raihan (2026) provide evidence that rider category may influence speeding and law adherence, making behavioural analysis essential for professional delivery contexts. These studies suggest that p-hailing safety can be improved when artificial intelligence is used to identify risky road

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conditions, monitor rider readiness, and examine unsafe riding practices. However, the findings also imply that AI should be applied carefully because road safety involves technical, behavioural, and human judgement factors. For p-hailing riders, safety systems based on AI may support earlier warning, better platform policy, and more targeted safety intervention.

AI, Machine Learning, and Digital Technologies for Transport Infrastructure Resilience

The theme of AI, machine learning, and digital technologies for transport infrastructure resilience shows that recent studies give strong attention to prediction, response, and system stability in transportation networks. Zhu et al. (2026) examine spatiotemporal resilience prediction for the Maritime Silk Road transportation network using graph neural networks, indicating that resilience is not only related to physical infrastructure strength but also to how transport nodes and routes interact across space and time. Principi et al. (2026) focus on seismic risk mapping for existing highway bridges at a regional scale through Artificial Neural Networks, showing that machine learning can support risk identification for large groups of infrastructure assets instead of relying only on individual bridge assessment. Zhao et al. (2025) develop automatic response prediction within a digital twin framework for regional bridge groups, suggesting that digital representation of infrastructure can help anticipate how bridges may respond under different stress conditions. Together, these studies show that transport resilience has moved from reactive maintenance toward predictive and intelligent decision support. For p-hailing services, this discussion is relevant because rider safety depends not only on individual riding behaviour but also on the reliability of roads, bridges, traffic networks, and supporting mobility systems.

The findings from these studies suggest that artificial intelligence can improve infrastructure resilience by processing large-scale, complex, and dynamic data more efficiently than conventional assessment methods. Zhu et al. (2026) demonstrate that graph neural networks are useful for modelling transportation networks because such networks are naturally formed by connected routes, ports, hubs, and movement flows. This allows resilience prediction to consider both spatial relationships and temporal changes. Principi et al. (2026) similarly show that Artificial Neural Networks can be applied to regional bridge seismic risk mapping, where large numbers of bridges need to be assessed according to vulnerability and possible hazard exposure. Zhao et al. (2025) strengthen this approach by using a digital twin framework, where bridge groups can be digitally simulated to predict responses and support faster decision-making. When combined, these studies suggest that AI-supported infrastructure resilience is built through prediction, simulation, optimisation, and adaptive control. In the context of p-hailing, these findings may support safer routing, better disruption management, and improved awareness of risky infrastructure zones. For example, bridge vulnerability, traffic network disruption, and energy-related mobility failure may indirectly affect delivery riders who depend on continuous road access and stable urban mobility systems.

Overall, this theme highlights that AI and digital technologies provide important support for safer and more resilient transportation infrastructure. Zhu et al. (2026) show the importance of spatiotemporal prediction in transport network resilience, while Principi et al. (2026) demonstrate that Artificial Neural Networks can support seismic risk assessment of existing highway bridges at a regional level. Zhao et al. (2025) indicate that digital twin technology can be used to predict infrastructure response automatically. The combined discussion shows that infrastructure safety is no longer limited to physical inspection, but increasingly involves real-time data, predictive modelling, and intelligent response systems. For p-hailing services, this is important because safe delivery operations require roads and transport networks that remain functional during hazards, congestion, infrastructure stress, or system failure. AI applications may therefore help platforms, transport authorities, and urban planners to identify weak infrastructure points, anticipate disruptions, and design safer mobility environments for riders. However, the studies also imply that technical accuracy, data quality, and system integration are important because unreliable prediction may lead to weak safety decisions.

Intelligent Transport Systems, Traffic Estimation, and Mobility Simulation

The theme of intelligent transport systems, traffic estimation, and mobility simulation shows that artificial intelligence is increasingly applied to improve transport decision-making, movement prediction, and system performance. Hao and Levinson (2026) examine mode choice in decentralized shared mobility by using a bagging-enhanced heterogeneous ensemble method, suggesting that machine learning can improve understanding of how users choose between mobility options. Jiang et al. (2026) focus on the transfer process between high-speed rail and metro systems in railway hubs through simulation and machine learning, indicating that passenger movement, transfer efficiency, and station performance can be evaluated more systematically. Amo-Boateng and Adu-Gyamfi (2026) address real-time traffic state estimation by developing an accelerated spatial conflation approach for connected vehicle data using GPUs. Together, these studies show that intelligent transport systems depend on the ability to process mobility data accurately, estimate traffic conditions, and simulate travel behaviour. For p-hailing services, these findings are relevant because rider safety and service efficiency are affected by road congestion, route selection, transport network conditions, and the behaviour of other users within the same mobility environment.

The findings indicate that machine learning and simulation-based methods can support more responsive and data-informed transport systems. Hao and Levinson (2026) show that ensemble learning can strengthen mode choice estimation by combining different predictive models, which may provide better accuracy than a single modelling approach. Jiang et al. (2026) demonstrate that simulation and machine learning can evaluate the full transfer process in railway hubs, where passenger flow, waiting time, walking distance, and connection efficiency may affect overall transport performance. Amo-Boateng and Adu-Gyamfi (2026) show that connected vehicle data can be spatially aligned and processed quickly using GPU-based methods, allowing real-time statewide traffic state estimation. These studies share the same concern with improving transport intelligence through faster analysis, higher prediction accuracy, and better system visibility. In the p-hailing context, such technology can assist platform operators and urban mobility planners to identify congested areas, improve routing decisions, and reduce exposure to risky traffic conditions.

Overall, this theme highlights that intelligent transport systems can support p-hailing safety by improving the prediction and management of transport movement. Hao and Levinson (2026) contribute by showing how machine learning can estimate mode choice in shared mobility environments, while Jiang et al. (2026) show that simulation and machine learning can evaluate complex transfers between high-speed rail and metro services. Amo-Boateng and Adu-Gyamfi (2026) add that connected vehicle data and GPU acceleration can support real-time traffic state estimation across a large area. Combined, these studies suggest that AI applications may improve mobility safety through better traffic awareness, faster data processing, and more accurate modelling of transport behaviour. For p-hailing riders, this may help reduce travel uncertainty, improve route planning, and support safer decisions during peak periods or network disruption. The discussion also implies that reliable data integration is important because weak data matching, inaccurate simulation, or poor model performance may reduce the usefulness of intelligent transport systems.

Shared Mobility, Equity, Sustainability, and Transport Governance

The theme of shared mobility, equity, sustainability, and transport governance highlights that safety in AI-enabled transport systems cannot be separated from cybersecurity, social access, and fairness in mobility use. Almuhammadi et al. (2026) discuss the need for a NIST CSF-based cybersecurity profile for artificial intelligence and machine learning systems in transportation networks, showing that intelligent mobility services require structured protection against cyber risks, system misuse, and data-related threats. This finding is highly relevant because AI-based transport services depend on digital platforms, connected data, automated decision-making, and continuous information exchange between users, vehicles, infrastructure, and service providers. In another direction, Merchán-Núñez et al. (2026) examine peer-to-peer paid carpooling in Bogotá as a route toward sustainable shared mobility, suggesting that shared mobility can reduce dependence on private vehicle use and support more efficient travel behaviour when properly managed. Tang et al. (2026) add a social justice perspective by examining unequal streets and unequal journeys, showing that shared mobility systems may reproduce hidden inequalities if access, infrastructure, affordability, and spatial distribution are not fairly addressed. For p-hailing services, this is important because platform-based delivery riders operate inside the same transport ecosystem, where cybersecurity weaknesses, unequal road environments, and unsustainable mobility patterns can influence daily safety.

The findings and discussion from these studies suggest that governance is a central requirement for safe and sustainable shared mobility. Almuhammadi et al. (2026) show that AI and machine learning systems in transportation networks need cybersecurity profiles that can identify, protect, detect, respond, and recover from threats. This is especially important because AI systems may handle sensitive mobility data, travel patterns, user identity, payment information, and operational decisions. Merchán-Núñez et al. (2026) provide a different but related contribution by showing that peer-to-peer paid carpooling can become part of sustainable shared mobility when social acceptance, travel demand, and practical mobility needs are considered. Tang et al. (2026) further show that shared mobility is not automatically equal, since unequal street conditions, uneven infrastructure, and hidden social mechanisms may influence who benefits from such services. In relation to p-hailing, these three studies collectively indicate that safety also includes digital security, fair access to mobility infrastructure, and protection from system-level exclusion.

Overall, this theme shows that AI applications for enhancing safety in p-hailing services require an integrated view of transport governance. Almuhammadi et al. (2026) demonstrate that cybersecurity frameworks are necessary because AI and machine learning systems in transportation networks depend on reliable and protected digital infrastructure. Merchán-Núñez et al. (2026) show that shared mobility can support sustainability through peer-to-peer paid carpooling, especially when mobility behaviour and user needs are properly understood. Tang et al. (2026) highlight that shared mobility may contain hidden inequalities, meaning that transport innovation may not benefit all users equally without careful planning and policy support. In practical terms, AI can help p-hailing platforms improve monitoring, routing, risk detection, and service coordination, but such applications must operate within strong cybersecurity and governance structures. The discussion indicates that safety cannot be treated only as an individual rider issue because platform design, road environment, cybersecurity readiness, and urban inequality also shape risk exposure.

Table 3: Thematic Synthesis for Research Themes

Theme	Focus of Discussion	Articles Included
Theme 1: AI-Driven Road Safety, Driver Behaviour, and Human Risk Detection	Studies using AI, deep learning, or behavioural analysis to improve road safety, visibility, driver monitoring, fatigue detection, cognitive impairment detection, and rider behaviour.	Zhang et al. – *A driving visibility index for evaluating urban road driving safety based on point cloud data* Fu et al. – *MEDS-Net: Meta-Evidential Dual-Stream Network for Multimodal Few-Shot Driver Fatigue Detection* Ghoreishi et al. – *Quad-Tree-Based Driver Classification Using Deep Learning for Mild Cognitive Impairment Detection* Sadat & Raihan – *Do Riding Behavior, Speeding, and Law Adherence Differ between Professional and Nonprofessional Riders?*
Theme 2: AI, Machine Learning, and Digital Technologies for Transport Infrastructure Resilience	Studies applying AI, ANN, GNN, digital twins, reinforcement learning, and predictive models to improve the resilience, safety, and performance of transport networks and infrastructure.	Zhu et al. – *GNN-based spatiotemporal resilience prediction for Maritime Silk Road transportation network* Principi et al. – *Mapping seismic risk of existing highway bridges at a regional scale using Artificial Neural Networks* Zhao et al. – *Automatic response prediction in a digital twin framework for regional bridges group* Tang et al. – *Heuristic-Guided Safe Multi-Agent Reinforcement Learning for Resilient Spatio-Temporal Dispatch of Energy-Mobility Nexus Under Grid Faults*
Theme 3: Intelligent Transport Systems, Traffic Estimation, and Mobility Simulation	Studies focusing on transport system optimization, traffic estimation, railway–metro transfer performance, connected vehicle data, and machine learning-based mobility modelling.	Hao & Levinson – *Estimating mode choice in decentralized shared mobility: A bagging-enhanced heterogeneous ensemble method* Jiang et al. – *Performance Evaluation of the Full Transfer Process between High-Speed Rail and Metro in Railway Hubs: A Simulation and Machine Learning Approach* Amo-Boateng & Adu-Gyamfi – *A novel approach for accelerated and accurate spatial conflation of connected vehicle data*

		on GPUs and its application to real-time statewide traffic state estimation
Theme 4: Shared Mobility, Equity, Sustainability, and Transport Governance	Studies examining shared mobility systems, carpooling, mobility inequality, sustainability, and cybersecurity governance in AI-enabled transport systems.	Almuhammadi et al. – *A NIST CSF-based cybersecurity profile for AI and machine learning systems in transportation networks* Merchán-Núñez et al. – *Exploring peer-to-peer paid carpooling in Bogotá: A path to sustainable shared mobility* Tang et al. – *Unequal streets, unequal journeys: The hidden mechanisms of shared mobility*

Discussion and Conclusion

This systematic literature review aimed to examine the application of artificial intelligence (AI) for enhancing safety in p-hailing services by synthesising scholarly evidence published between 2020 and 2026. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, relevant studies were systematically identified from the Scopus and Web of Science databases. The review focused exclusively on peer-reviewed journal articles published in English and at the final publication stage. A total of 45 studies met the inclusion criteria and were subjected to qualitative thematic analysis. The review was guided by four research questions that sought to understand how AI technologies are applied to improve road safety and human risk detection, strengthen transport infrastructure resilience, support intelligent transport systems and traffic management, and influence governance, sustainability, and equity within shared mobility environments. Through this process, the review addressed the fragmented nature of existing literature and provided a comprehensive understanding of AI applications that contribute to safer p-hailing operations.

The findings revealed four interconnected themes that collectively demonstrate the expanding role of AI in transportation safety. First, AI-driven road safety applications focus on monitoring rider behaviour, detecting fatigue, identifying cognitive impairment, and assessing environmental risks to reduce accident likelihood. Second, AI, machine learning, and digital technologies are increasingly utilised to improve transport infrastructure resilience through predictive modelling, digital twin systems, reinforcement learning, and risk assessment tools. Third, intelligent transport systems employ simulation techniques, traffic estimation models, and real-time mobility analytics to enhance route planning, traffic management, and transportation efficiency. Finally, studies related to shared mobility, sustainability, equity, and governance indicate that safety extends beyond operational performance to include cybersecurity, fair access to mobility services, and sustainable transportation practices. Across these themes, several common patterns emerged. Most studies adopted advanced AI techniques such as machine learning, deep learning, artificial neural networks, graph neural networks, simulation modelling, and predictive analytics. The findings also suggest a gradual shift from reactive safety management towards predictive and preventive approaches, where risks can be identified and mitigated before incidents occur. From a theoretical perspective, the literature demonstrates the growing integration of technological, behavioural, infrastructural, and governance dimensions in understanding transportation safety. From a practical perspective,

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AI applications increasingly support real-time decision-making, risk prediction, infrastructure monitoring, and operational optimisation within mobility ecosystems.

This review contributes to the field by consolidating diverse and fragmented research streams into a unified framework specifically focused on p-hailing safety. While previous studies have generally examined individual AI technologies or specific transportation contexts, this review synthesises evidence across multiple domains and demonstrates how safety outcomes are influenced by interactions between human behaviour, intelligent technologies, transport infrastructure, and governance systems. The four-theme classification developed in this study offers a structured perspective for understanding current developments and future research directions in AI-enabled transportation safety. Furthermore, the review highlights an important knowledge gap in the existing literature, where relatively limited attention has been given to the direct application of AI technologies within p-hailing rider safety despite the rapid growth of the gig economy and platform-based delivery services. The findings suggest that future studies should explore integrated AI frameworks that combine behavioural monitoring, infrastructure intelligence, traffic analytics, and governance mechanisms within a single safety ecosystem. Greater attention should also be given to issues of algorithm transparency, cybersecurity, privacy protection, data quality, and ethical implementation to ensure that technological advancement translates into meaningful safety improvements. Overall, this review demonstrates that AI has substantial potential to transform safety management in p-hailing services and provides an important foundation for researchers, policymakers, and platform operators seeking to develop safer, more resilient, and sustainable mobility systems.

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