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Article

A Review of Vehicle Wheel Misalignment Detection Techniques

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Abstract

Wheel (mis)alignment is one of the factors influencing vehicle safety, tire wear, and energy efficiency. While alignment procedures are well established in automotive workshops, recent advances in sensing, connectivity, and data-driven methods have led to renewed academic interest. This goes against existing research, which remains fragmented around vehicle types and methodologies. This study conducts a scoping review of wheel alignment monitoring and detection methods, with a focus on passenger vehicles. Guided by PRISMA-ScR, 453 studies were identified, of which 386 were excluded and 13 were duplicates and thus removed, resulting in a small number remaining for thematic analysis. Three dominant methodological approaches emerged: (i) traditional measurement methods, (ii) sensor-based vehicle dynamics analysis, and (iii) data-driven methods employing machine learning and vehicle telemetry. The findings revealed limited research on vehicle applications, especially for intelligent, integrated, and scalable alignment technologies and real-time, in-service monitoring applications. Other challenges included data quality, calibration, and cost-effectiveness. Therefore, the development of an integrated real-time wheel misalignment detection and reporting framework grounded in systems engineering and enterprise architecture principles is proposed.

Keywords: wheel misalignment; vehicle dynamics; sensing techniques; intelligent monitoring

1. Introduction

Wheel misalignment is a recurring issue in vehicle maintenance that often leads to increased tire wear, decreased fuel efficiency, and unsafe handling dynamics [1]. This condition, which affects the inclination of the car wheels relative to its chassis and the road surface, results from factors such as impacts of the wheel on road conditions, suspension degradation, and manufacturing tolerances [2]. Misalignment in parameters like toe, camber, and caster is particularly detrimental in heavy commercial vehicles (HCVs) and high-speed systems, whereby minor deviations can have significant stability and safety consequences [3,4].

Traditionally, wheel alignment assessment has been conducted in workshop environments using static measurement tools such as laser alignment systems and mechanical gauges [5]. While accurate under static conditions, these systems require skilled labor and periodic inspection schedules; furthermore, they are inherently reactive, only identifying misalignment once the vehicle is already significantly exhibiting wear or drift symptoms.

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In light of increasing demands for predictive maintenance, particularly in the context of smart mobility and autonomous systems, these traditional approaches fall short [1].

Despite its practical importance, academic research on wheel alignment, particularly for passenger vehicles, remains relatively limited. Existing studies are dispersed across multiple domains, including railway engineering, commercial vehicles, and intelligent transportation. In recent years, emerging technologies such as inertial sensors, computer vision, and Internet of Things (IoT) have introduced new possibilities for continuous and automated alignment monitoring. These include the use of onboard inertial measurement units (IMUs), steering angle sensors, and vehicle telemetry to detect deviations in vehicle dynamics or drift behaviors [6,7]. In addition, simulation-based methods such as dynamic adhesor have been used to measure the vehicle wheel's adhesion force and behavior when rolling [8]. Furthermore, the IPG TruckMaker® has been employed to train classifiers such as Support Vector Machines (SVMs) to distinguish between aligned and misaligned states [3,4]. These emerging approaches offer the potential for real-time, automated detection but are often constrained by the lack of publicly available data, validation in real-world conditions, and integration with fleet-level monitoring systems.

Despite these advances, current research on vehicle wheel misalignment remains dispersed across mechanical, electrical, and data science domains, with limited attempts at standardization. This gap is especially relevant in connected and autonomous vehicles (CAVs) and fleet management contexts, where real-time diagnostics and system interoperability are crucial [1,9]. Given the heterogeneity of vehicle types, sensing modalities, and analytical methods, a systematic literature review focused on effect comparison or performance ranking is currently premature. Instead, a scoping review was preferred to map the breadth of existing research. Accordingly, this review addresses the following research questions (RQs):

- RQ1: How has publication on wheel alignment evolved in recent years?
- RQ2: What are the main research themes addressed in the scientific literature?
- RQ3: What are the future prospects and emerging challenges for wheel alignment technology?

Given the emerging and fragmented nature of the research field, we adopt a systematic review methodology in accordance with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analysis—systematic reviews), where evidence is heterogeneous and exploratory mapping is required. In particular, there is a noticeable gap in studies addressing system-wide integration, that is, how misalignment data collected from multiple vehicles or platforms can be centralized, managed, and acted upon to support fleet-scale predictive maintenance strategies. The remainder of this paper is structured as follows: Section 2 outlines the methodology employed for article selection, inclusion and exclusion criteria, and the thematic coding procedures employed. Section 3 presents a synthesis of detection techniques, categorizing them into traditional, sensor-based, and AI-enhanced approaches. Section 4 identifies key research gaps and limitations within the existing literature, and Section 6 concludes the review and offers recommendations for future research directions.

2. Materials and Methods

This study addresses the research questions (RQ1–RQ3) by adopting a mixed-methods PRISMA review approach, combining bibliometric analysis using Biblioshiny, a web interface for the bibliometrix R package Version 4.3.0 [10], to provide both a map of the intellectual structure of the field and an interpretation of vehicle wheel misalignment detection research. The PRISMA 2020 [11] framework ensures transparency and reproducibility in the article selection process. It comprises four main stages: database selection, search string formulation, article screening, and eligibility assessment. The search strategy was developed to capture the peer-reviewed research published in the last decade and a half (15 years) and focused on vehicle wheel misalignment detection and its associated diagnostic technologies. Following the PRISMA-ScR guidelines, the review not only documents existing vehicle wheel misalignment detection technologies but also examines the broader distribution of research and derives key trends across technologies and vehicle platforms.

2.1. Search Strategy

A comprehensive literature search was conducted across selected scientific databases, including Scopus, IEEE Xplore, Web of Science, and Emerald Insight. Search strings combined terms related to wheel alignment, misalignment, toe and camber angles, sensing technologies, IoT, and intelligent monitoring systems. The search process initially yielded 453 records, from which 13 duplicates were removed. After title and abstract screening and assessment for relevance and technical depth, 54 full-text articles were retained for detailed analysis based on their focus on misalignment detection and real-world vehicular applicability.

A combination of keywords and Boolean operators (“wheel alignment” OR “wheel misalignment”) AND (“toe angle” OR “camber” OR “caster”) AND (“vehicle dynamics” OR “sensor” OR “fault detection” OR “monitoring”) was used to retrieve relevant studies. The search was limited to articles written in English and published in academic journals or conference proceedings. The PRISMA flow process guiding this selection is summarized in Figure 1.

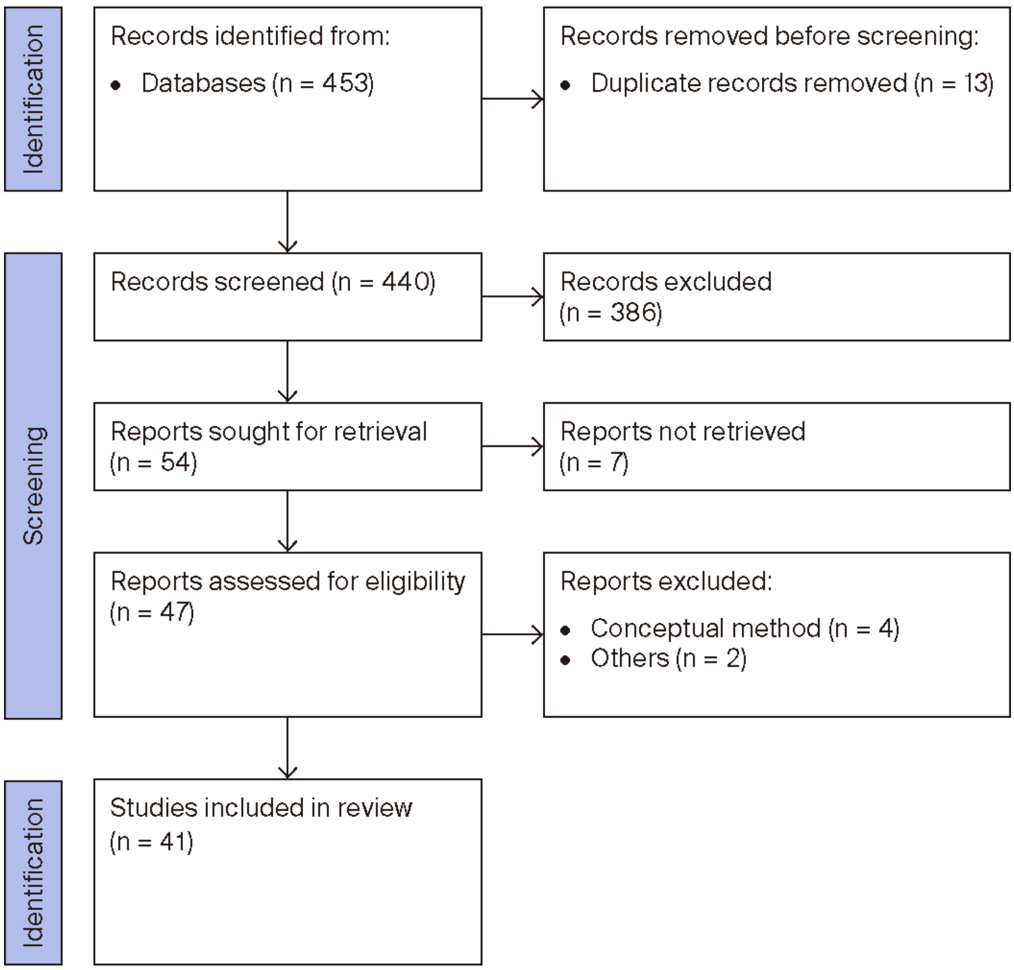

Figure 1. PRISMA method.

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2.2. Eligibility Criteria

Following the initial search, 13 duplicate records were removed, leaving 440 unique articles. To ensure relevance, articles were selected based on a defined set of inclusion and exclusion criteria. The inclusion criteria were as follows: (i) the article presents a technical approach or evaluation related to vehicle wheel misalignment detection; (ii) the focus is on land vehicles (e.g., passenger cars, trucks, or autonomous vehicles); (iii) the study involves a hardware implementation, sensor-based framework, simulation environment, or algorithmic approach to detection; and (iv) the article is peer-reviewed and written in English.

Exclusion criteria ruled out studies focused on alignment correction or repair services, as well as those centered on human behavioral aspects. Additionally, the final full-text assessment excluded research concerning aerial vehicles, rail transport, editorials, and papers lacking sufficient methodological detail. Duplicate entries and articles with inaccessible full texts were also removed.

2.3. Screening and Selection Process

Records were screened in two stages: title/abstract screening followed by full-text assessment. During this process, 386 records were further excluded for failing to meet the inclusion criteria. The remaining 54 studies were retained for full-text review and included in the final analysis.

2.4. Data Chart and Synthesis

For each of the 54 included studies, data were extracted descriptively, including publication year, vehicle type, methodological approach, and application domains. Hence, the thematic synthesis grouped the studies into three core categories based on their approach, which are described in the next section.

3. Results

The 54 studies included in this review were thematically categorized into three main groups based on their methodological approach: (i) traditional detection techniques, (ii) sensor-integrated systems, and (iii) data-driven or simulation-based methods. This section synthesizes the key developments, applications, and limitations within each category.

3.1. Traditional Detection Techniques

Conventional wheel alignment techniques remain widely used in workshop environments. These include manual tools such as camber/caster/toe angle gauges, optical alignment devices, and laser-based systems that evaluate the spatial orientation of the wheels relative to manufacturer specifications. Lee and Choi [12] proposed a method to detect toe misalignment in real time by modeling the lateral tire force and aligning moment; the authors used recursive least squares and vehicle simulation without needing extra sensors beyond the vehicle's existing dynamics. Blagojević, Živković [5] demonstrated the use of photogrammetric calibration systems in enhancing the precision of mechanical alignment lines. The authors used CMM and reference chassis to certify alignment lines for assembly and service rigs, improving static alignment accuracy and consistency across devices.

In the study by Cheng, Chen [13], laser displacement sensors (2D/1D) provided a triangulation system and IPC was used to measure wheelset profile (flange width/height and diameter). Similarly, Young, Hsu [14] employed fixed optical tools or goniometers (photo/mechanic) for measuring camber alignment, which are workshop-based methods. The authors of [15] used a mechanical measurement system in a workshop or static rig.

They designed and developed a dynamic adhesor for measuring the hydraulic control of the wheel head, enabling adjustment to the vehicle wheel's toe-in and camber relative to a cylinder simulating the road conditions. However, the adhesor was simulated digitally and did not account for real wheel-rolling conditions.

Despite their reliability under controlled conditions, these systems are inherently stationary, labor-intensive, and non-continuous, making them unsuitable for real-time applications. Errors in calibration, human oversight, and variability in alignment platforms contribute to measurement uncertainty, especially when used across varying road and load conditions.

3.2. Sensor-Based Misalignment Detection

Advances in embedded vehicle sensors have enabled the development of onboard misalignment detection systems, leveraging real-time data from inertial measurement units (IMUs), steering angle sensors, wheel speed encoders, and yaw rate sensors [6,7]. Basic sensor-based detection methods have been discussed in [2,16], whereby the authors designed a small, portable wheel alignment monitoring system using sensors, a micro-controller, and an Android mobile app. Both studies emphasize usability and real-time monitoring via IoT.

Instances of more advanced sensor-based detection methods are presented by Broderick, Britt [6], who used a Gaussian Process model trained on steering correction data to estimate lateral drift due to toe misalignment. Similarly, Hong, Hussin [17] used IMU monitoring on a train bogie to detect dynamic track misalignment, which proved effective in detecting track-induced deviations in vehicle motion. Yongxu, Tan [18] used dynamic testing with sensors (shaft torque and vibrations) to assess misalignment. This method enhanced drift detection using a combination of IMU and GPS-derived curvature patterns. Furthermore, Bohari, Hafiz [1] proposed an embedded IMU + CAN bus smart alignment monitoring system that utilizes a network of vehicle sensors to detect deviations from normal wheel posture. The onboard sensors record steering and IMU data for continuous posture monitoring and demonstrate real-time misalignment trend detection in test vehicles.

Vision systems have been reported in [7,19,20]. In [7], a vision-based positioning system capable of detecting wireless charging coil misalignment was developed, offering analogies to mechanical misalignment localization. The mobile robot uses camera and misalignment coils for millimeter-precision positioning over charging pads to achieve millimeter-scale positioning error (<5 mm). Similarly, Wang, Li [21] reported an absolute error of less than 0.2 mm for their tire thread measurement method based on machine vision.

Huber, Preindl [19] presented an optical camera + edge detection method, involving an onboard wheel-well camera that captures tread cross-section. In canny-edge-based outline extraction, adaptive calibration is achieved via tread indicators. The method achieved a mean absolute error < 0.6 mm, demonstrating its feasibility for real-time remaining useful life estimation. Müller and Voegtle [22] used a sensor-based method with image analysis to detect steering angles during alignment. Their method can be considered traditional if purely image-based.

Sensor-based detection methods are advantageous due to their non-invasiveness, real-time monitoring capabilities, and ease of integration with vehicle CAN bus systems. However, their performance remains sensitive to sensor drift, road texture, payload, and environmental noise. Robust signal filtering and multi-sensor fusion algorithms are often required to achieve reliable misalignment estimates.

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3.3. Data-Driven and Simulation-Based Approaches

A growing number of studies have applied machine learning (ML) and simulation environments to detect misalignment patterns using synthetic or real-world datasets. These approaches utilize platforms like IPG TruckMaker®, CarSim, and Simulink to simulate toe, camber, or caster faults and train classification models [3,4,9]. Burande, Grandhe [4] developed a supervised learning model using curvature and steering torque features, demonstrating high accuracy in toe misalignment detection. Chandran, Grandhe [3] extended this work to examine the roll behavior of trucks under thrust angle misalignment. Both studies emphasized the need for data diversity and realistic load modeling in simulation environments.

The authors of [3] proposed a digital twin-based framework combining finite element modeling and diagnostic signal processing for early fault detection in suspension components. Tang, Shi [23] used an embedded IMU + ECOC SVM classifier as an energy-efficient WAWMS with dual wake up, IMU self-calibration, PCA-based feature extraction, and support vector classification. Their system achieved ~93.2% accuracy in real-world misalignment detection (varied toe angles). Grandhe, Kumar [24] used a simulation and model-based classifier (e.g., SVM or equivalent) trained on simulation data. Alrejjal and Ksaibati [25] used dynamics simulation or sensors to quantify rollover risk.

The machine learning approaches used in [26,27] provide data on vehicle pattern generalization, GPS speed, and brake signals that is scalable across vehicle types and used to inform filtering. However, ML models are highly dependent on data quality, simulation fidelity, and labeling accuracy. Additionally, transferability to real-world deployment is limited due to model overfitting and a lack of public validation datasets.

A comparative summary of the key research themes discussed is presented in Table 1.

Table 1. Comparative summary of key research themes.

Approach	Strength	Limitations	Reference Studies
Traditional methods	High static accuracy Mature technology	Non-continuous, operator-dependent, no in-motion data	[5,14,15]
Sensor-based systems	Real-time, embedded, uses existing vehicle architecture	Sensor drift, influenced by load/terrain, data fusion needed	[7,19,22]
AI/ML-based approach	Simulation-rich, scalable, high classification accuracy	Lack of real-world data, validation gaps, high computation	[3,4,9]

4. Analysis

The bibliometric analysis of the overall search strings (Boolean combination) offered a comprehensive view of the evolving research landscape related to all types of vehicles' (train, aerial, and robot) wheel alignment systems, revealing distinct trends, thematic clusters, and shifts in scholarly focus over time.

Figure 2 shows a pie chart representing various transport sectors with wheel alignment applications. The analysis revealed that many studies emanated from non-vehicle-specific infrastructure (39%) and aircraft landing gear systems (36%). Even though these studies are not directly related to vehicles, they contribute to sensor technologies, structural monitoring, and fault detection systems, which are relevant in this study. Additionally, studies on railway and train systems account for 17% of the studies reviewed in this article. Railway and train systems provide important insights that are related to wheel track monitoring and predictive maintenance systems, which are equally important in the context of real-time wheel misalignment detection and reporting systems.

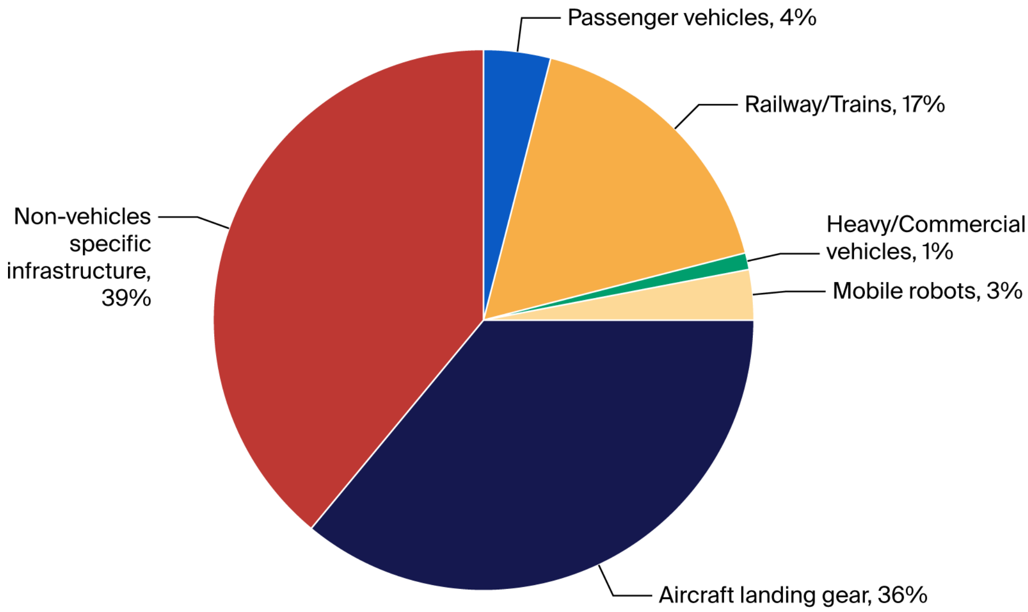

Figure 2. Pie chart representing various transport sectors with wheel alignment applications sourced from database.

Contrary to this, a small fraction of studies directly focused on technologies in passenger vehicles (4%) and heavy or commercial vehicles (1%). The limited number of studies on vehicle technologies underlines a clear gap in the development of real-time wheel misalignment detection and reporting systems in the automotive industry.

Nonetheless, studies on aviation, railway systems, and general monitoring systems are still important and relevant to the current study, as they provide transferable methodologies, sensor technologies, and frameworks that can be customized for use in the development of real-time wheel misalignment detection and reporting systems.

4.1. Scientific Production and Citation Trends

The volume of scientific output (shown in Figure 3) in this domain is recorded from 2010 and has shown steady growth from 2013, with a sharp spike in publications post-2020, peaking in 2023. This suggests increasing research interest, likely driven by advancements in transport automation, vehicle dynamics, and smart infrastructure. Interestingly, the average citations per year peaked early but remained relatively stable afterward, indicating consistent academic attention and engagement. Table 2 presents a summary of the main research focus and specific approaches adopted in the studies.

4.2. Geographic and Country Distributions

When analyzing the total items sourced from the database (440), the country-level publication counts (Figures 4 and 5) reveal that China, India, Malaysia, the UK, and the USA are key contributors. Notably, India shows the most dramatic rise in publication volume after 2020, suggesting a recent surge in research investments or interest in transportation infrastructure. However, when it comes to impact, measured by citations, China and the UK lead with 117 and 81 citations, respectively. This indicates that, while India's output is growing rapidly, China and the UK maintain stronger academic influence.

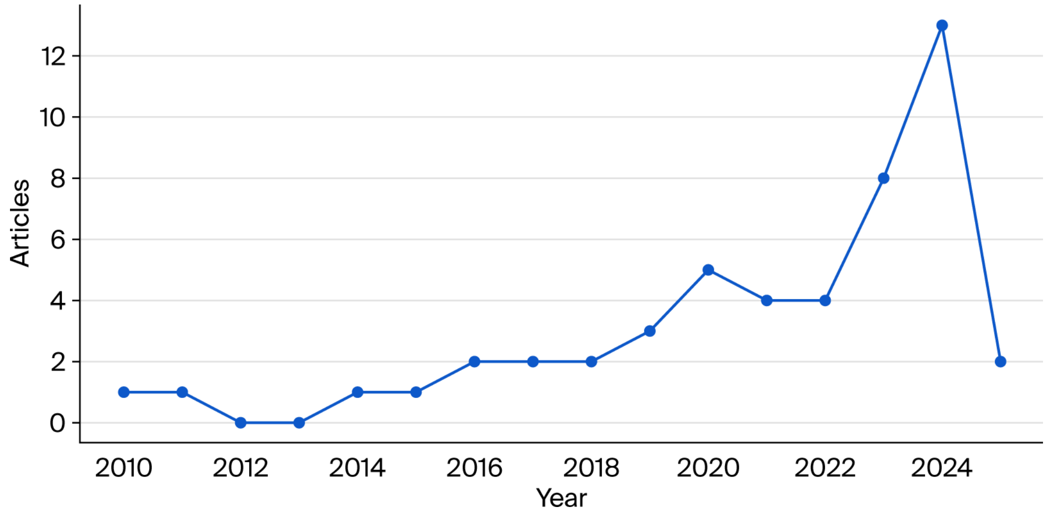

Figure 3. Annual scientific production.

Table 2. Summary of the main research focus.

Authors (Year)	Application Domain	Focus Area(s)	Research Approach/Methodology
Broderick, Britt [6]	Automotive sensing	Vehicle pose estimation, sensor calibration	Gaussian processes applied to LiDAR data; real-time calibration and validation against GPS
Hong, Hussin [17]	Railway infrastructure	Track misalignment detection	IMU-based sensing; field testing on passenger trains; signal analysis
Ding Jianming, Lin Jianhui [28]	Vehicle dynamics	Motion stability detection	Signal decomposition (IEMD + Hilbert transform); time-varying damping ratio
Cheng, Chen [13]	Railway transportation	Wheelset size and geometry detection	Laser displacement sensing; calibration modeling; field experiments
Blagojević, Živković [5]	Automotive maintenance	Wheel alignment calibration	Photogrammetry-based calibration and certification method
Cortes and Kim [7]	Mobile robotics	Misalignment-aware positioning	Computer vision + misalignment-sensing coils; LQR control; experimental validation
Bhagyalekshmi, Maya [29]	Railway inspection	Track fault and misalignment detection	Image processing, ultrasonic and vibration sensors; solar-powered robotic platform
Huang, Chen [30]	Driver monitoring	Unsafe driving and wheel-hand interaction	Wearable magnetic sensing; activity classification; large-scale road experiments
Amato and Marino [31]	Electric vehicles	Fault-tolerant wheel/motor control	Distributed PI control; fault detection and isolation; simulation-based evaluation
Dutta, Harrison [32]	Railway switches	Switch misalignment and actuation	Multibody dynamic modeling; closed-loop control; co-simulation

Table 2. *Cont.*

Authors (Year)	Application Domain	Focus Area(s)	Research Approach/Methodology
Hu, Zhang [33]	Railway drivetrain	Cardan shaft misalignment diagnosis	Acceleration signal analysis; DTCWPT; SNR optimization; simulation + experiments
Chen and Yang [34]	Electric vehicles	Torsional vibration suppression	Genetic algorithm optimization; adaptive fuzzy PID control
Gonera and Napiórkowski [35]	Automotive wear	Tire wear vs. wheel geometry	Experimental analysis correlating mileage, geometry, and wear
Alrejjal and Ksaibati [25]	Road safety	Rollover risk under misalignment and weather	Vehicle dynamics simulation; multinomial regression modeling
Ardakani and Cheshmehzangi [36]	Smart transport	Big data analytics for transport systems	Machine learning, clustering, and regression; conceptual and applied review
Bezin, Sambo [37]	Railway dynamics	Wheel–rail alignment and profile preprocessing	CAD and measured data preprocessing; multibody simulation
Chen and Hu [38]	Aerospace systems	Actuator misalignment and fault tolerance	Sliding Mode Control; Lyapunov stability analysis; numerical simulations
Prakash and Tadepalli [39]	Railway SHM	Track damage and misalignment detection	Acoustic sensing (DAS); ML-based signal classification; systematic review
Bohari, Hafiz [1]	Automotive monitoring	Smart wheel alignment monitoring	Embedded sensors; microcontroller-based real-time monitoring
Burande, Grandhe [4]	Heavy vehicles	Toe misalignment detection	Data-driven ML (SVC); TruckMaker simulations; feature synthesis
Chandran, Grandhe [3]	Heavy vehicle safety	Toe and thrust misalignment impact on rollover	Vehicle dynamics simulation + analytical modeling
Chen, Yu [40]	Autonomous vehicles	Path planning and tracking control	APF + MPC + fuzzy driver model; co-simulation
He, Xu [41]	Driver fatigue	Non-visual fatigue detection	Multi-sensor fusion; BiLSTM with attention; naturalistic driving data
Herbuś, Dymarek [9]	Machine diagnostics	Misalignment and early fault detection	Digital Shadow concept; vibration sensing; Simulink-based modeling
Alaswed and Sinha [42]	Railway maintenance	Condition-based maintenance (CBM)	Reliability analysis (Weibull, FMEA, and FTA); sensor-based framework
Arshad, Lodi [43]	Automotive suspension	Alignment and geometry optimization	Systematic review; AI, evolutionary algorithms, and quantum optimization

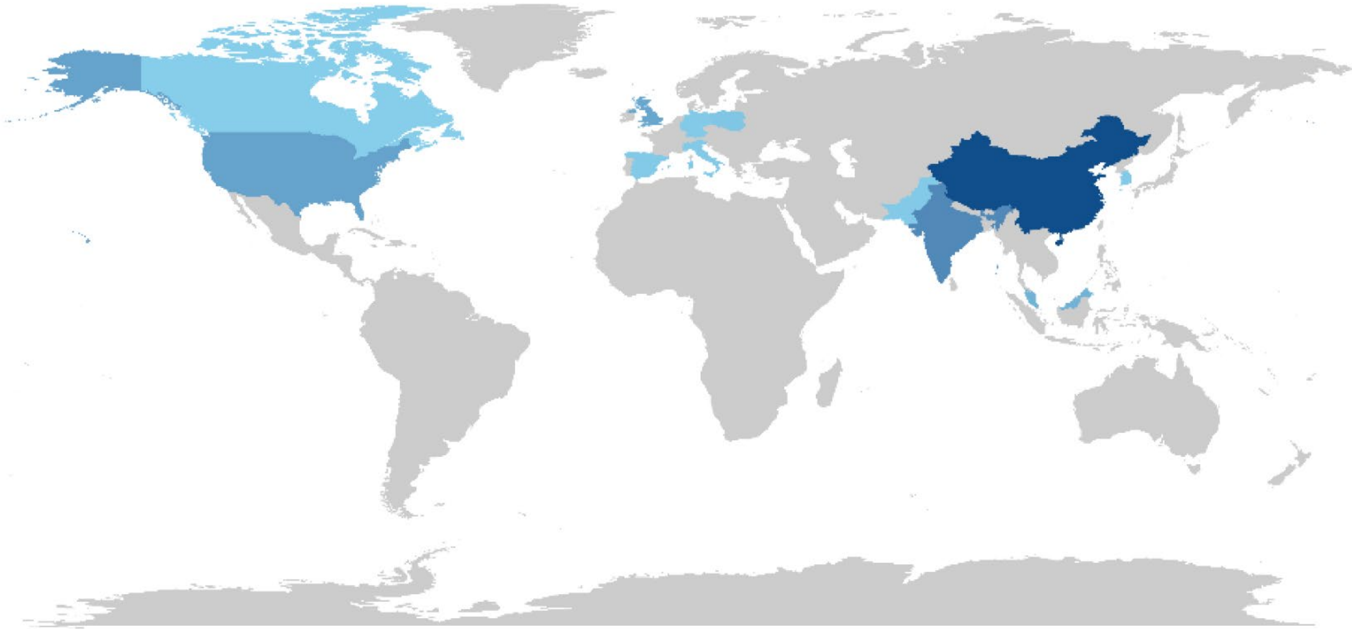

Figure 4. World map showing publication distribution.

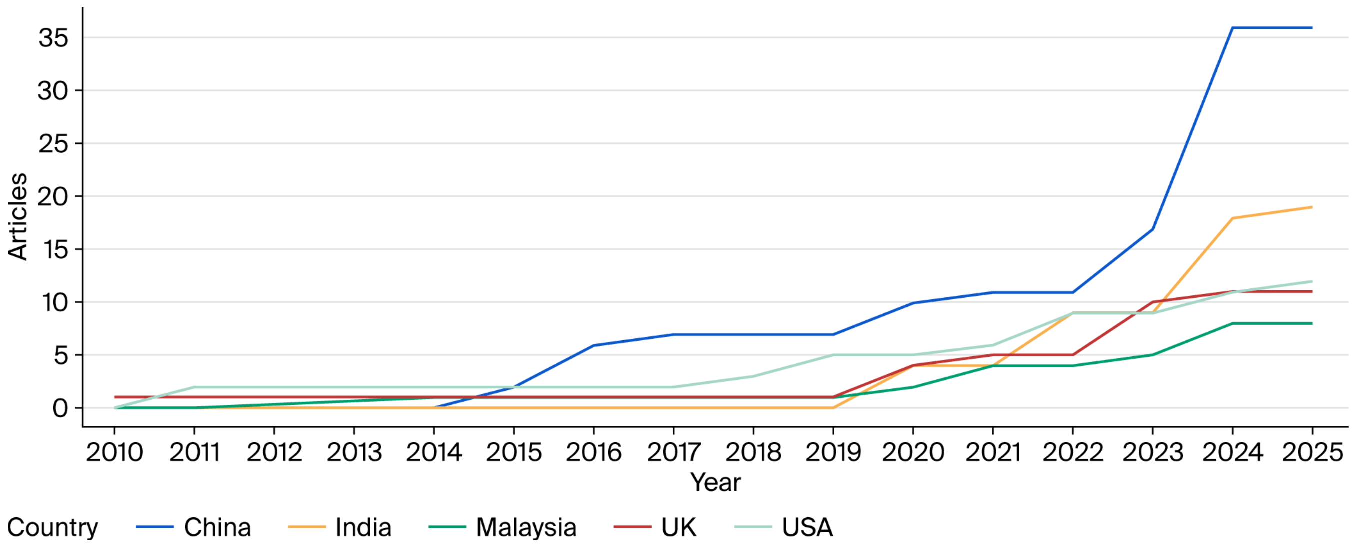

Figure 5. Country publication production over time.

4.3. Thematic Structure and Conceptual Evolution

The thematic and keyword analysis highlights several well-defined clusters. Figure 6 shows motor themes (high relevance and development). Topics like alignment, wheels, and tires form the technical backbone of this field. These are robust themes with wide research application, central to rail–vehicle interface design and performance optimization. Regarding basic themes, concepts such as railroads, railroad transportation, vehicle wheels, and rails remain foundational. While these topics are highly relevant, their lower development density suggests they are either well-established or under-explored opportunities for innovation.

Regarding emerging themes, terms like wheel alignment, monitoring systems, and camber appear in the bottom-left quadrant, signaling newer, less-developed areas that are beginning to attract scholarly attention, particularly in the context of smart rail systems and AI-driven diagnostics. Regarding niche themes, specialized topics like image processing, navigation, and Computer Aided Design, though well-developed, have limited connectivity to the core themes, implying targeted applications or isolated subfields.

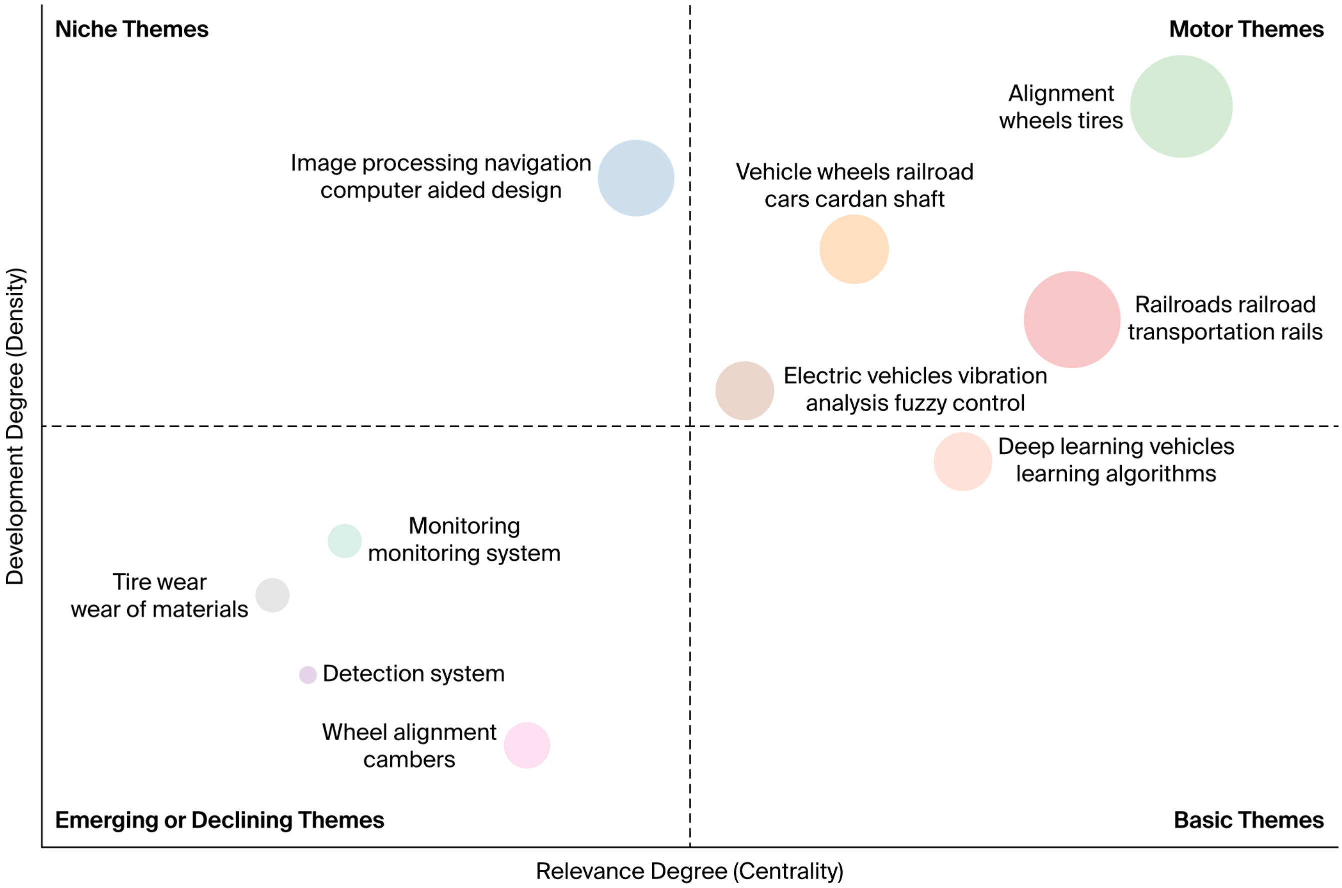

Figure 6. Conceptual evolution.

4.3.1. Keyword Distribution Analysis Using a Tree Map Tree-Map

The tree-map shown in Figure 7 provides a visual summary of the most frequently occurring keywords across the analyzed literature in wheel alignment and underscores that the field is dominated by traditional mechanical and railroad-alignment themes, with sensor-based monitoring steadily growing and AI/ML approaches emerging but still underrepresented. It also highlights gaps in human-centered research and the adaptation of alignment systems to new mobility paradigms like electric and autonomous vehicles.

The large (%) dominance of alignment (15.8), railroads (12.6), and wheels (11.6) shows a well-established body of work, but it also suggests saturation in traditional topics. Emerging blocks like deep learning (4.2), IoT (2.1), and image processing are smaller (3.2), suggesting that AI/ML and IoT-enabled approaches remain relatively underdeveloped and present clear opportunities for future research. The low frequency of human-centered terms (e.g., humans (2.1) and health monitoring (2.1)) implies a research gap in human-in-the-loop and ergonomics studies within wheel alignment contexts. Similarly, the relatively small presence of electric vehicles indicates a gap in adapting alignment/monitoring solutions for EV platforms, which have different suspension and wheel load characteristics.

4.3.2. Keyword Trends and Topic Growth

Keyword usage reflects the shifting priorities within the domain over time. The word frequency plot (Figure 8) and trend timeline show that earlier focus areas like railroad tracks and rails have stabilized, while alignment, wheels, and vehicle wheels have seen a consistent upward trajectory since 2020. The rise of keywords like deep learning, fault detection, and image processing indicates a growing interdisciplinary infusion of AI and computer vision into traditional mechanical and civil engineering domains.

Figure 7. Tree-map.

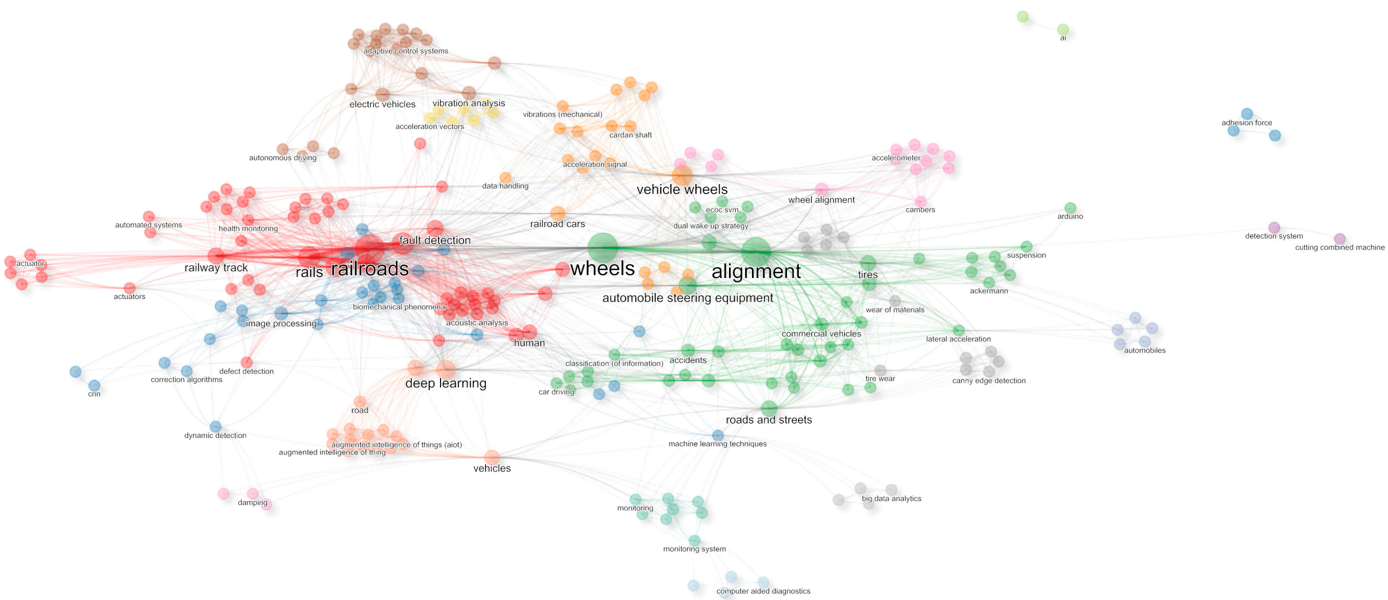

Figure 8. Thematic map.

Similarly, the word cloud shown in Figure 9 further validates these trends, with alignment emerging as the most prominent term, followed by railroads, wheels, vehicle wheels, and railroad transportation—demonstrating the interconnectedness of rail infrastructure and vehicular mechanics as central research pillars.

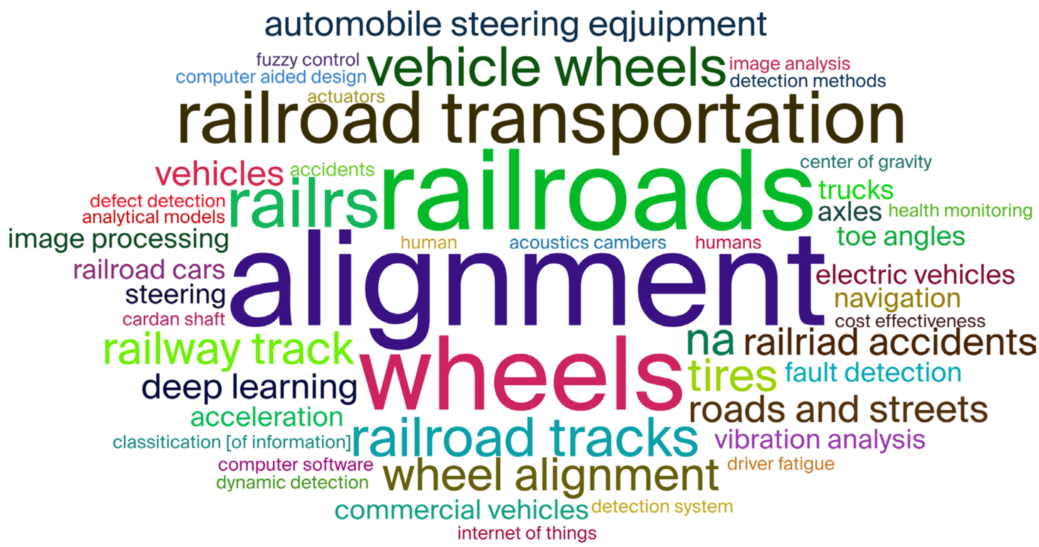

Figure 9. World cloud.

5. Gap Analysis

The scoping literature review uncovered that there is a gap in the use of traditional methods regarding wheel alignment. Primarily, traditional methods cannot predict when a vehicle's wheel alignment will be out of specification. Furthermore, in traditional methods, wheel alignment checks are performed following a particular schedule which is mileage- or time-dependent, and alignment accuracy heavily relies on technician or human intervention. Hence, there is a risk of vehicle safety issues with these methods as it is more likely for a vehicle to run on uneven tires for a longer time before problems are noticed. In addition, traditional methods only provide static measurement and completely ignore deflections that occur when a vehicle is in motion. There is also no communication loop to inform stakeholders why the misalignment occurred and its extent.

Sensor-based misalignment detection can detect anomalies. However, these sensors cannot make a distinction between misalignment from other causes like potholes and tire wear. Sensor-based misalignment detection operates in isolation and is not integrated with vehicle telematics, workshops, and cloud platforms. Additionally, sensors are heavily dependent on raw data transmission and cannot perform complex real-time tasks.

Simulators struggle to replicate real-world incidents like chaotic vibrations due to tire wear. Most simulators are trained on clean data and struggle when it comes to random events such as potholes, gravel roads, and strong winds. Data-driven approaches require large amounts of well-defined data on wheel misalignment, which are extremely difficult to obtain. It was established that even though AI, IoT, and image processing technologies are developing quickly, their application, especially in wheel misalignment detection and reporting systems, is still restrained. In addition, there are limited research studies on smart, automated detection and reporting systems that analyze data in real time.

6. Discussion

Although wheel alignment is a fundamental aspect of vehicle maintenance, our systematic search identified only ~25 car-specific papers. This apparent scarcity reflects the historical dominance of research in railway and heavy-vehicle contexts, where misalignment directly impacts safety and logistics. In contrast, car wheel alignment has traditionally been addressed through standardized workshop procedures, limiting the need for academic publications.

Moreover, much automotive research remains proprietary within manufacturers and workshops, creating a publication bias. Importantly, the concentration of car-focused studies in the past five years suggests an emerging trend toward IoT-enabled, vision-based, and AI-driven solutions for passenger vehicles. Thus, rather than a limitation, the small number of papers highlights a significant research gap that warrants further investigation.

6.1. Evolution of Wheel Alignment Research (RQ1)

Research into wheel alignment has undergone a clear trajectory over the past two decades. Early contributions, particularly in the 2010s, focused on traditional measurement approaches such as photogrammetry and optical calibration systems. For example, Blagojević, Živković [5] demonstrated the calibration of wheel alignment lines using a simple photogrammetry approach, providing precise results in controlled environments. However, while this approach is accurate, it lacks scalability and real-time capability. Moving forward, in the mid-2010s, there was a notable transition toward embedded sensors and real-time monitoring.

Hong, Hussin [17] pioneered an IMU-based misalignment detection method in train track alignment, while Cortes and Kim [7] investigated autonomous positioning using vision and coil sensors. Such studies exemplify the shift from static to in-service measurement. This marked the beginning of in-service measurement approaches, moving diagnostics out of workshops and into operational settings.

The largest growth in publications occurred after 2020, consistent with the bibliometric analysis. Recent works such as those by Tang, Shi [23], who proposed a miniature wireless monitoring system, and Burande, Grandhe [4], who developed a data-driven toe misalignment detector for heavy vehicles, illustrate the integration of low-cost IoT sensors and machine learning techniques. Overall, publication activity has intensified, reflecting broader trends in predictive maintenance and intelligent transportation.

6.2. Dominant Research Themes (RQ2)

The review identifies three methodological clusters, namely traditional methods, sensor-based systems, and AI/ML-based approaches, as discussed in Sections 3.1–3.3. Cross-cutting themes include the use of computer vision [20,21]. The bibliometric keyword map in Figure 6 confirms this structure by showing a tightly knit group of terms centered around “alignment”, “wheels”, “railroads”, and “deep learning”, revealing the convergence of mechanical and AI-based approaches in transportation.

6.3. Future Prospects (RQ3)

The literature points to strong prospects but also significant challenges for wheel alignment technologies. Prospects include the following:

- Multi-sensor fusion and edge AI, where embedded models combine IMU, GPS, and vision data to provide real-time alignment monitoring;
- Digital twins and sim-to-real transfer, allowing synthetic training data to augment limited real-world datasets [24];
- Fleet-wide predictive maintenance platforms, where telematics aggregate alignment data to support maintenance scheduling [9];
- Low-power IoT systems, enabling scalable adoption in commercial fleets [2].

Key challenges include the following:

- Real-world validation and sensor reliability.

Although emerging systems, like the in-vehicle wireless alignment monitor developed in [23], have shown promising classification accuracy under controlled testing conditions, long-term validation under diverse real-world driving dynamics is missing. Similarly, the authors of [1] demonstrated real-time alignment trend detection using IMU and CAN-bus data but did not report performance under variable loads or terrain and lacked assessments over extended vehicle lifecycles. Additionally, foundational sensor-based models, such as those proposed in [6], address yaw drift in Gaussian process estimation. Hence, without robust self-calibration strategies and a real-world validation system, accuracy and reliability over time remain uncertain, limiting practical deployment.

- Reliance on simulation and absence of scalable architecture.

Most AI/ML-based systems [3,4] rely on simulation-generated datasets, achieving high misalignment classification accuracy in synthetic scenarios but lacking validation in actual driving conditions. This leads to the risks of model overfitting and poor generalizability. Furthermore, no public field datasets exist to benchmark these models. Meanwhile, even sensor-based embedded systems lack integration with flee-wide telemetry and centralized data platforms. This can be testified as fleet management applications are absent from the reviewed studies.

Misalignment detection is largely confined to isolated vehicle units, with no edge-to cloud data framework or predictive analytics pipeline proposed. While muti-sensor fusion has been proposed and is widely recognized in autonomous vehicle research, it remains underutilized in this domain. These gaps collectively impede scalable and reliable deployment within OE or fleet-scale contexts.

7. Research Plan to Close Identified Gaps

The review identified a significant lack of passenger-vehicle-focused research, particularly within the South African automotive context, where infrastructure variability, road conditions, and maintenance challenges differ considerably from those reported in developed countries. With existing approaches predominantly focusing on isolated sensing technologies, there remains a gap for integrated and scalable wheel misalignment. To address this gap, the present study proposes the development of an integrated real-time wheel misalignment detection and reporting framework grounded in Design Science Research (DSR), system engineering principles, and the Federal Enterprise Architecture Framework (FEAF). Shown in Figure 10, this framework illustrates the interaction between physical sensing infrastructure, intelligent analytics processes, and stakeholder-oriented discussion within the governance mechanism.

The conceptual framework is composed of sensing, learning, and infrastructure subsystems. The sensor layer acquires dynamic operational data associated with wheel behavior and vehicle motion. The learner subsystem applies intelligent analytics methods to identify and classify misalignment conditions based on extracted features and learned behavioral patterns. Finally, the infrastructure layer enables real-time communication, reporting, and maintenance support through connected platforms and intelligent transportation systems.

Beyond sensing and intelligent diagnostic capabilities, the proposed framework also requires a robust data governance architecture to ensure secure, traceable, and compliant operation. Governance mechanisms such as regulatory compliance and centralized data repository enhance accountability in AI-driven wheel misalignment diagnostics, particularly safety-critical applications.

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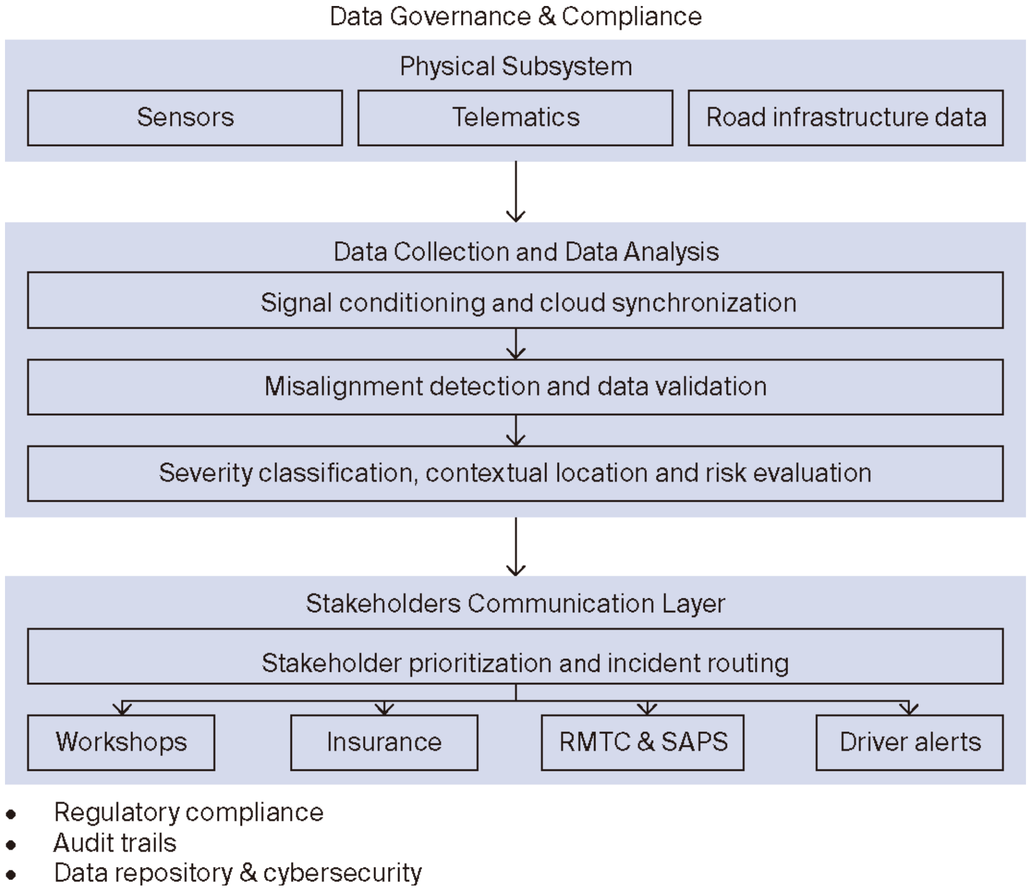

Figure 10. Conceptual framework for the proposed integrated real-time wheel misalignment detection and reporting system.

8. Conclusions

The review revealed that there is limited research on vehicle wheel misalignment detection techniques. Four major gaps were identified: the lack of systems for real-time detection and reporting; limited integration of sensing, data processing, and reporting systems; underutilization of AI, IoT, and multi-sensor fusion; and non-availability of scalable data and monitoring frameworks. The review also revealed that traditional methods in use cannot predict when a vehicle's wheel alignment will be out of specification, and sensors are not integrated with vehicle telematics, workshops, and cloud platforms. In addition, sensors are heavily dependent on raw data transmission and cannot perform complex real-time tasks.

The study presents a conceptual framework that offers a solution to address the identified gaps through the development of a real-time wheel alignment detection and reporting system. The conceptual framework integrates Systems Engineering Architecture principles and Federal Enterprise Architecture Framework (FEAF) reference domains consisting of performance, data, application, infrastructure, and security. Future research should continue to integrate automated sensing, AI-driven diagnostics, and advanced material systems into rail and vehicle alignment technologies.

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