infrastructures

MDPI

Systematic Review

Floating Car Data in Transportation: A Survey of the Literature

Sara Siverio *, Roberto Ventura and Benedetto Barabino

Department of Civil Engineering, Architecture, Land, Environment and Mathematics (DICATAM), Università di Brescia, 25123 Brescia, Italy
* Correspondence: s.siverio@unibs.it; Tel.: +39-333-405-9116

Abstract

Floating Car Data (FCD) are increasingly used to analyse mobility patterns and support transport-system management, but the evidence remains fragmented across heterogeneous applications, sensing technologies, and data-processing methods, particularly regarding road-infrastructure monitoring. This study presents a systematic literature review and structured evidence map of FCD research published between 2010 and 2025. Following PRISMA methodology, Scopus and Google Scholar were searched using the exact expression "floating car data". The search retrieved 2127 records; after bibliographic harmonisation, duplicate removal, title-and-abstract screening, full-text retrieval, and eligibility assessment, 165 publications were included. The studies were classified through a top-down framework covering application domain, sensing technology, processing approach, validation method, geographical region, deployment scale, and integration with Pavement Management Systems (PMSs). Traffic-state estimation and mobility-planning applications covered 100 publications (60.6%), whereas infrastructure monitoring was the primary domain in 20 studies (12.1%). GPS or GNSS data were used in 128 publications (77.6%), while accelerometers, gyroscopes, or inertial measurement units were reported in 29 studies (17.6%). Only 15 publications (9.1%) described operational or real-time deployment, and explicit PMS-oriented integration was identified in only 9 studies (5.5%). The findings show that FCD research is methodologically mature for traffic and mobility applications but remains comparatively fragmented for pavement-condition assessment. The review therefore proposes an operational pathway linking accelerometric data acquisition, preprocessing, normalization, fleet-level aggregation, validation, data fusion, and PMS decision-making. These results highlight that the principal research gap concerns not sensor availability, but the development of standardized, transferable, and operationally validated frameworks for network-wide pavement monitoring.

Keywords: floating car data; pavement management systems; road condition monitoring; accelerometric data; data fusion; intelligent transportation systems

Check for updates

Academic Editor: Pedro Arias-Sánchez

Received: 17 February 2026
Revised: 18 July 2026
Accepted: 22 July 2026
Published: 26 July 2026

1. Introduction

Floating Car Data (FCD) have become an essential source of information for understanding mobility dynamics and supporting the management of transport systems. Typically collected through GPS-enabled onboard devices, FCD provide temporally dense vehicle trajectories that enable high-resolution analyses of traffic behavior. Compared to traditional static sensors, such as loop detectors or fixed cameras, FCD offer wider spatial coverage, higher temporal flexibility, and lower implementation and maintenance costs, which have favored their widespread adoption in large-scale applications. Within Intelligent Transportation System (ITS) architectures, they are increasingly framed as integrated data sources enabled by positioning, communication, and processing technologies, and are extensively used in real-time traffic modeling, congestion prediction, travel-time estimation, and route optimization [1,2]. Recent advances in Internet of Things (IoT) connectivity, sensor miniaturization, and artificial intelligence-driven analytics are further amplifying the role of FCD as a versatile and scalable component of modern ITS [1,2].

Survey-oriented contributions and existing reviews primarily describe FCD as a technology-driven source for traffic monitoring and mobility management, with particular emphasis on positioning systems, communication infrastructures, and traffic-flow indicators. As a result, the spectrum of FCD applications, especially those related to infrastructure monitoring, has received comparatively less systematic attention. Although several studies have explored the potential of onboard sensors, including accelerometers, to detect surface irregularities and pavement distress, their use remains highly heterogeneous across the literature: different sensing setups, processing techniques, and data-fusion strategies coexist, often without standardized validation procedures. Consequently, the integration of such signals into operational Pavement Management Systems (PMSs) remains insufficiently documented and only partially understood.

Addressing this gap is relevant both theoretically and practically. From a theoretical perspective, leveraging FCD (in particular accelerometric signals) for infrastructure assessment shifts the paradigm from purely traffic-oriented indicators toward a physically grounded interpretation of vehicle–road interaction, enabling connections between microscale dynamic responses and network-level pavement performance. From a practical perspective, a more systematic exploitation of FCD for road condition monitoring could support the transition from episodic, inspection-based maintenance to continuous, data-driven diagnostics, with implications for maintenance prioritization, resource allocation, and predictive intervention planning.

The paper synthesizes methodological trends, identifies limitations and operational challenges, and highlights research directions that may support the development of scalable and integrated pavement management solutions.

Unlike previous reviews that primarily adopt traffic-oriented [3] or technology-centered perspectives [1], this study proposes a top-down analytical framework explicitly connecting FCD applications, sensing technologies, and data processing methodologies, with particular emphasis on the underexplored role of accelerometric FCD for scalable pavement monitoring.

Following this introduction, Section 2 describes the adopted methodology, including the search strategy and analytical framework. Section 3 presents the results of the systematic review, offering a descriptive overview of the selected studies and the proposed classification scheme. Section 4 discusses the implications of the findings and outlines future research perspectives. Finally, Section 5 concludes the survey.

2. Materials and Methods

2.1. Review Design and Reporting Framework

This study adopted a systematic literature review with a structured evidence-mapping component to examine the use of Floating Car Data (FCD) across transportation research. The review considered a broad range of application domains, including traffic monitoring, mobility analysis, transport planning, logistics, road safety, environmental assessment, and road-infrastructure monitoring. Within this general perspective, specific attention was devoted to the comparatively underexplored use of vehicle-derived inertial and accelerometric data for pavement-condition assessment.

The review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses statement (PRISMA) [4]. Reporting of the search strategy was additionally informed by the PRISMA-S recommendations. Comparable systematic-review approaches have previously been applied in transportation research [5–7].

The conceptual scope, eligibility criteria, search strategy, screening framework, and analytical dimensions were defined before substantive screening. No predetermined target number of publications, thematic quota, or desired proportion of studies was established. Consequently, the final composition of the review corpus resulted exclusively from the consistent application of the predefined eligibility criteria.

2.2. Operational Definition and Scope of Floating Car Data

For the purposes of this review, core FCD were defined as georeferenced observations generated by moving motor vehicles and containing, at minimum, spatial position and time information, together with speed, direction, trajectory, or related mobility attributes where available.

Enriched FCD were defined as core FCD combined with measurements obtained from onboard vehicle systems or devices, including Controller Area Network (CAN), On-Board Diagnostics (OBD), telematics units, odometers, inertial measurement units, accelerometers, gyroscopes, event-data recorders, and black-box systems. Vehicle-borne complementary sensing was also considered within the extended FCD scope when georeferenced measurements were acquired during vehicle operation and could be associated with a vehicle trajectory or travelled road segment. This category included observations collected through smartphones, onboard cameras, and other mobile sensing devices installed in or carried by circulating vehicles.

This extended definition was adopted to reflect the evolution of FCD from conventional positioning-based trajectories towards heterogeneous and sensor-enriched vehicle data. Nevertheless, a clear distinction was maintained between observations generated by moving vehicles and data collected exclusively through external sensing systems.

Fixed roadside detectors, stationary cameras, inductive loops, radar systems, mobile-network data, satellite or aerial imagery, Unmanned Aerial Vehicle data, and infrared thermography were therefore not independently classified as FCD sources. Studies employing these technologies remained eligible when external observations were integrated with, used to validate, or used to benchmark vehicle-derived data. Conversely, studies relying exclusively on fixed, aerial, remote, or otherwise external sensing systems were excluded from the primary review corpus.

This review does not aim to provide an exhaustive synthesis of the broader vehicle-borne sensing literature. Its systematic evidence base is limited to publications explicitly positioned by their authors within the FCD domain and retrieved through the predefined exact-phrase search.

2.3. Information Sources and Search Strategy

The systematic search was conducted using two complementary bibliographic sources: Scopus and Google Scholar. Scopus was selected as the principal structured database because of its broad coverage of peer-reviewed literature in transportation, engineering, computer science, data science, and infrastructure management. Google Scholar was searched through Harzing's Publish or Perish to complement the structured database and identify scholarly publications that might not be consistently indexed in Scopus.

The searches were last conducted and exported on 3 January 2026. The review covered publications issued between 1 January 2010 and 31 December 2025. The lower temporal boundary was established before the formal search following a preliminary scoping analysis, which showed a marked increase in publications explicitly referring to Floating Car

Data from approximately 2010 onwards. Publications issued in 2026 were excluded to avoid analysing an incomplete publication year and to ensure that all annual observations referred to complete publication periods.

A deliberately specific search strategy was adopted. The exact expression searched in both bibliographic sources was "floating car data". In Scopus, the query was implemented as TITLE-ABS-KEY ("floating car data"), thereby searching the expression in titles, abstracts, and indexed keywords. Publication-year, language, and document-type filters were applied directly within the Scopus interface. Disciplinary relevance and metadata consistency were subsequently verified at record level after export.

Google Scholar was searched through the general search function of Harzing's Publish or Perish using the same exact expression, the publication-year interval 2010–2025, and a maximum return of 1000 records. The search returned 966 records and therefore did not reach the configured maximum-result threshold.

The acronym "FCD" was not searched independently because it is used in several unrelated scientific domains and would have substantially reduced search specificity. Broader or adjacent expressions, including "probe vehicle data", "connected vehicle data", "smartphone sensing", "accelerometer", "black box", "pavement monitoring", and "road-condition monitoring", were likewise not incorporated into the formal search string. This decision produced a clearly bounded and reproducible corpus of publications explicitly positioned by their authors within the FCD literature. Consequently, adjacent vehicle-borne sensing studies not explicitly associated with the FCD terminology were outside the systematic evidence base and were used only for contextual comparison where relevant.

Publications identified outside the two predefined searches were used only for conceptual background or methodological comparison. These publications were identified during the preliminary scoping phase, through reference-list checking of eligible studies, and through targeted reading on specific conceptual or methodological issues that emerged during manuscript development. They were not included in the study-selection counts, quantitative mapping, classification frequencies, or evidence synthesis. The systematic evidence base was therefore defined exclusively by the Scopus and Google Scholar searches.

Table 1 summarises the bibliographic sources and search strategy.

Table 1. Bibliographic sources and search strategy.

Source	Search Environment	Field Searched	Exact Query	Temporal Coverage and Limits	Final Search Date	Records Retrieved
Scopus	Scopus web interface	Title, abstract, and indexed keywords	TITLE-ABS-KEY ("floating car data")	2010–2025; database filters applied directly and eligibility rechecked at record level	3 January 2026	1161
Google Scholar	Harzing's Publish or Perish, general search	General scholarly search	"floating car data"	2010–2025; maximum return set to 1000 records	3 January 2026	966

The two sources were searched using the same exact phrase and temporal coverage to ensure consistency across databases. Scopus provided the structured bibliographic component of the search, while Google Scholar was used as a complementary source to broaden coverage beyond records consistently indexed in Scopus.

2.4. Bibliographic Data Harmonisation, Duplicate Removal, and Preliminary Eligibility

The two bibliographic exports were merged into a single review database. Original source information, source-specific identifiers, and unmodified bibliographic fields were retained to preserve provenance and enable reconstruction of the identification process.

Before duplicate detection, the bibliographic fields were harmonised to reduce non-substantive differences between database records. Textual information was converted to a consistent character representation; leading, trailing, and repeated spaces were removed;

letter case was standardised; and differences in punctuation, quotation marks, dash variants, and special characters were normalised. Digital Object Identifiers were converted to lowercase and stripped of URL prefixes and extraneous characters. Titles were separately normalised for matching purposes, while their original forms were retained for reporting and manual verification.

Duplicate identification followed a hierarchical framework. Records were first matched using exact DOI correspondence. **Duplicate identification followed the hierarchical framework summarised in** Table 2**.** Records without a DOI, or with incomplete DOI information, were subsequently compared through exact normalised-title matching. Remaining potential duplicates were identified using combinations of title similarity, author information, publication year, source title, volume, issue, and page information.

Table 2. Hierarchical framework for bibliographic harmonisation and duplicate identification.

Priority	Matching or Adjudication Criterion	Normalisation or Evidence Used	Decision Procedure
1	Exact DOI correspondence	DOIs converted to lowercase and stripped of URL prefixes, spaces, and extraneous characters.	Records grouped as candidate duplicates; bibliographic consistency verified before consolidation.
2	Exact normalised title correspondence	Case, punctuation, repeated spaces, dash variants, quotation marks, and non-substantive special characters normalised.	Applied when DOI was missing, incomplete, or inconsistent; matching records verified before consolidation.
3	High title similarity combined with author and year	Title similarity assessed jointly with first author, co-author pattern, and publication year.	Candidate pairs manually inspected; no record removed solely on approximate similarity.
4	Extended bibliographic correspondence	Source title, volume, issue, page range, publisher, and document type compared.	Used to distinguish database duplicates from genuinely distinct but bibliographically similar publications.
5	Conference–journal relationship assessment	Dataset, study area, method, experiment, and reported findings compared across related reports.	Reports retained separately when the later publication added relevant data, methods, validation, or findings; otherwise consolidated at report level.
6	Master-record selection and provenance retention	Completeness of DOI, abstract, keywords, source information, and other metadata assessed.	The most complete record retained as master; all contributing source identifiers and duplicate-group assignments preserved.

Duplicate identification combined exact bibliographic matching with progressively broader record-level comparison. Approximate similarity was used only to identify candidate pairs, while final consolidation required verification of bibliographic correspondence and substantive overlap between the publications.

Approximate bibliographic similarity was used only to identify candidate duplicate pairs and did not result in automatic removal. Candidate matches were inspected individually to determine whether they represented duplicate database entries, related conference and journal publications, extended versions of previous studies, or genuinely distinct contributions. When duplicate records were confirmed, one master record was retained, with preference given to the version containing the most complete bibliographic information. The provenance of all contributing database records was nevertheless preserved.

Publications with similar titles were retained separately when they reported different datasets, geographical settings, methodological developments, experiments, or substantive findings. Through this procedure, 566 duplicate records were removed from the 2127 retrieved references, resulting in a deduplicated database of 1561 unique records.

The deduplicated records were then evaluated against predefined bibliographic eligibility criteria concerning publication period, language, publication type, disciplinary relevance, and availability of sufficient identifying information. Eligible publications were required to have been published between 2010 and 2025, to be written in English, and to be available as journal articles or individual conference papers reporting an original empirical, computational, experimental, modelling, or methodological contribution.

Reviews, systematic reviews, conference reviews, editorials, notes, books, book chapters, theses, dissertations, reports, patents, complete conference proceedings, and other non-original publication types were excluded from the primary corpus. Review articles could nevertheless be used to contextualise the results, compare classifications, and discuss previous syntheses, without being counted among the included original studies. During the preliminary scoping phase, review-type publications were also inspected to verify the existence and scope of previous syntheses on FCD and to refine the positioning of the present review; however, they were not treated as eligible original studies and were not included in any quantitative analysis.

When publication year, language, disciplinary classification, or document type was missing or inconsistent, the relevant information was verified using DOI metadata, publisher websites, journal or conference webpages, and other available bibliographic evidence. Records were not excluded solely because an abstract was unavailable. When the title and the remaining metadata indicated potential relevance, the record was conservatively retained for additional assessment.

Following duplicate removal and application of the preliminary bibliographic eligibility criteria, 1183 records entered title-and-abstract screening. The sequential number of records removed at each stage is reported in Figure 1 and in Section 3.1.

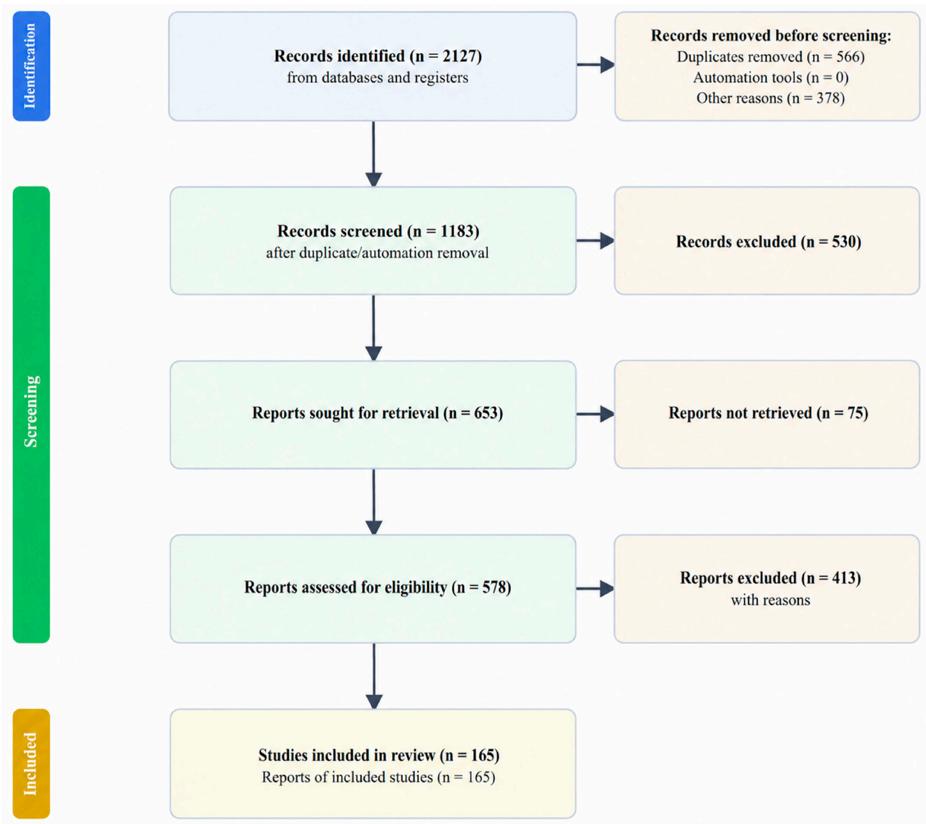

Figure 1. PRISMA flow diagram illustrating the identification, screening, full-text eligibility assessment, and inclusion of studies in the review.

The bibliographic and substantive eligibility criteria are summarised in Table 3.

Table 3. Eligibility criteria applied before and during substantive screening.

Dimension	Inclusion Criterion	Exclusion Criterion	Treatment of Ambiguity
Publication period	Publication issued between 1 January 2010 and 31 December 2025.	Publication issued before 2010 or after 2025.	Inconsistent or missing year verified through DOI, publisher, journal, or conference metadata.
Language	Full publication written in English.	Publication written in a language other than English.	Language verified from the full record or report when database metadata were incomplete.
Publication type	Journal article or individual conference paper indexed as such in the bibliographic source.	Review, systematic review, conference review, editorial, note, book, book chapter, thesis, dissertation, report, patent, complete proceedings, or other non-original type.	Ambiguous types verified using the publisher record and document structure.
Original contribution	Identifiable empirical, computational, experimental, modelling, or methodological contribution.	No identifiable original analysis, method, dataset, experiment, simulation, validation, or case study.	Unclear cases retained for manual or full-text assessment.
Disciplinary and application scope	Transportation, mobility, motor vehicles, road networks, traffic, logistics, safety, environmental transport analysis, or transport infrastructure.	Study clearly outside the transportation and road-infrastructure domain.	Multidisciplinary studies retained when the transportation component was substantive.
Role of FCD	FCD used as an analytical input, data source, validation or benchmarking source, or central methodological object.	FCD mentioned only in the introduction, background, related work, discussion of possible technologies, or future research.	Ambiguous analytical use assessed from the full abstract and, where necessary, the full text.
Data-source configuration	Core, enriched, or extended vehicle-derived FCD; mixed-source studies with a substantive vehicle-derived component.	Exclusive reliance on fixed, aerial, satellite, remote, or external sensing without vehicle-derived observations.	External data accepted when integrated with or used to validate vehicle-derived FCD.
Mobility mode	Motor-vehicle-derived observations present and analytically relevant.	Exclusively pedestrian, cycling, micromobility, or wheelchair data without a motor-vehicle component.	Mixed-mode studies retained when motor-vehicle FCD contributed substantively.

The eligibility criteria were applied consistently across bibliographic screening, title-and-abstract assessment, and full-text evaluation. When the available evidence was insufficient to support either inclusion or exclusion, records were retained for further assessment rather than excluded, thereby prioritising sensitivity and reducing the risk of false-negative decisions. Missing abstracts did not constitute an exclusion criterion; potentially relevant records were retained for manual or full-text assessment, whereas reports that could not be retrieved were recorded separately.

2.5. Deterministic Rule-Based Screening Framework with Manual Adjudication

Title-and-abstract screening was conducted through a deterministic rule-based framework developed to support the consistent and traceable application of the eligibility criteria across the bibliographic corpus.

The framework considered the title, abstract, author keywords, indexed keywords, source title, and document-type information available for each record. Before application of the decision rules, the textual fields were normalised to reduce lexical variation unrelated to substantive meaning. Text was converted to lowercase, repeated spaces were removed, typographical dash variants were harmonised, and punctuation, hyphens, slashes, underscores, and other non-alphanumeric characters were standardised. Multi-word expressions were assessed as normalised contiguous sequences, and matching was performed without regard to character case. Where lexical roots were required, terminal wildcard logic was used to capture morphological variants without substantially broadening the meaning of the searched terms.

The framework did not employ numerical relevance scores, probabilistic classification, machine learning ranking, random sampling, thematic quotas, or a predetermined number of publications to be retained. Instead, each record was evaluated against explicit Boolean conditions derived from the substantive inclusion and exclusion criteria and assigned to one of three outcomes: exclusion, potential eligibility, or uncertainty.

A record was classified as excluded only when the available metadata provided sufficiently clear evidence of ineligibility. This occurred when the publication was a review or another non-original contribution; when the study fell outside transportation, mobility, motor-vehicle, road-network, or transport-infrastructure research; when Floating Car Data were mentioned only as background, related work, or a hypothetical future source; when the study relied exclusively on fixed, aerial, remote, or external sensing without a vehicle-derived component; when the research concerned only pedestrian, cycling, micromobility, or wheelchair data without an analytically relevant motor-vehicle component; or when no identifiable original empirical or methodological contribution was present.

Mixed-source configurations were not excluded when vehicle-derived observations constituted a substantive component of the analytical input.

Potential eligibility was established when the metadata simultaneously indicated that the publication addressed FCD, as operationally defined in Section 2.2, within a transportation or road-infrastructure context; presented an identifiable original empirical or methodological contribution; and either treated FCD as an explicit central object of the study or used them substantively within the analytical procedure.

The complete exclusion, eligibility, and uncertainty logic are reported in Table 4.

Table 4. Formal screening outcomes and deterministic Boolean decision logic.

Screening Outcome	Formal Logical Condition	Operational Interpretation	Subsequent Action
Exclusion	NON_ORIGINAL_PUBLICATION OR OUTSIDE_TRANSPORT_SCOPE OR BACKGROUND_MENTION_ONLY OR EXTERNAL_SENSING_ONLY OR NON_MOTORISED_ONLY OR NO_ORIGINAL_CONTRIBUTION	At least one strong exclusion condition was clearly supported by the available metadata or verified evidence.	Exclude after targeted manual verification whenever contextual interpretation was required; assign one primary exclusion reason.
Potential eligibility	POSITIVE_FCD_SCOPE AND ORIGINAL_CONTRIBUTION AND (EXPLICIT_FCD_CENTRALITY OR ACTUAL_ANALYTICAL_USE)	The record concerned FCD within the defined transportation scope, reported an original contribution, and demonstrated either explicit centrality or substantive analytical use.	Retain for full-text retrieval and substantive eligibility assessment.
Uncertainty	NO STRONG EXCLUSION CONDITION SATISFIED AND POSITIVE ELIGIBILITY NOT ESTABLISHED	No strong exclusion condition was established, but the available title and abstract did not support eligibility with sufficient confidence.	Retain for manual reassessment; if ambiguity persisted, advance to full-text assessment rather than exclude.

The decision framework distinguished between records that clearly met a strong exclusion condition, records for which positive eligibility was supported, and records requiring additional assessment. The uncertainty category functioned as a conservative safeguard and did not constitute an intermediate relevance score.

Explicit FCD centrality was inferred when the relevant terminology occurred in the title or keywords in a manner consistent with the defined scope. Actual analytical use was assessed by determining whether FCD-related expressions occurred in a context describing data acquisition, collection, recording, preprocessing, analysis, integration, estimation, modelling, prediction, calibration, comparison, or validation. Evidence of an original contribution was identified through contextual information indicating the proposal, development, implementation, application, testing, evaluation, or validation of a method, model, dataset, experiment, simulation, or case study. The operational definitions, the lexical evidence associated with each condition, and the corresponding text-matching rules are summarised in Table 5.

https://doi.org/10.3390/infrastructures11080257

Table 5. Operational definitions, semantic evidence, and text-matching rules used in title-and-abstract screening.

Condition or Rule	Operational Lexical Evidence or Pattern	Contextual Requirement	Decision Function
POSITIVE_ FCD_SCOPE	floating car data; floating-car data; vehicle trajectories or observations explicitly described as FCD	Evidence required in title, abstract, author keywords, or indexed keywords and interpreted within a transportation context.	Activates positive scope only when the meaning is consistent with the operational definition in Section 2.2.
TRANSPORT_CONTEXT	traffic; transport *; road *; street *; highway *; motorway *; vehicle *; mobility; network *; route *; trip *; trajectory *; freight; logistics; pavement *; infrastructure	Term or equivalent contextual evidence required in the same record as FCD evidence.	Supports POSITIVE_FCD_SCOPE and prevents inclusion of records outside the intended domain.
VEHICLE_DERIVED _EVIDENCE	GPS; GNSS; probe vehicle; taxi; car; fleet; onboard; in-vehicle; CAN; OBD; telematics; odometer; accelerometer; gyroscope; IMU; inertial; black box; smartphone; vehicle-mounted camera	Smartphone and camera evidence accepted only when collection occurred during vehicle operation and was georeferenced or associated with a travelled road segment.	Distinguishes vehicle-derived observations from exclusively external sensing.
EXPLICIT_FCD_CENTRALITY	FCD terminology in the title or keywords; study objective explicitly framed around FCD	Occurrence evaluated together with the stated objective rather than by keyword presence alone.	Satisfies one branch of the positive-eligibility condition.
ACTUAL_ANALYTICAL_USE	collect *; acquire *; record *; obtain *; process *; analy *; integrate *; fuse *; estimate *; model *; predict *; reconstruct *; calibrate *; compare *; validate *; classify*; detect *; map-match *	FCD evidence required in the same sentence or within the two immediately adjacent sentences describing the analytical action.	Satisfies one branch of the positive-eligibility condition and excludes merely incidental mentions.
ORIGINAL_CONTRIBUTION	propos *; develop *; implement *; apply *; test *; evaluat *; validat *; experiment *; simulation; case study; method; model; algorithm; framework; dataset	Evidence interpreted contextually to confirm an original empirical or methodological contribution rather than a literature summary.	Required for potential eligibility.
BACKGROUND_MENTION _ONLY	background discussion; related work; literature overview; possible application; future work; technology mentioned without data use	Absence of acquisition, processing, modelling, validation, or other substantive analytical relation to FCD.	Strong exclusion when clearly demonstrated.
EXTERNAL_SENSING_ONLY	fixed detector; inductive loop; roadside radar; stationary camera; mobile-network data; satellite; aerial imagery; UAV; infrared thermography	Condition activated only when no substantive vehicle-derived observation was present.	Strong exclusion; mixed-source configurations retained.
NON_MOTORISED_ONLY	pedestrian; walking; bicycle; cycling; e-scooter; micromobility; wheelchair	Condition activated only when the study lacked an analytically relevant motor-vehicle component.	Strong exclusion; mixed-mode studies retained when motor-vehicle FCD were used.
NON_ORIGINAL _PUBLICATION	review; systematic review; survey article; editorial; commentary; book; chapter; thesis; report; patent; complete proceedings	Document-type evidence verified from bibliographic metadata and, where needed, the report itself.	Strong exclusion from the primary corpus; may remain usable as background literature.
TEXT NORMALISATION	lowercasing; removal of repeated whitespace; harmonisation of dash variants; standardisation of punctuation, hyphens, slashes, underscores, and non-alphanumeric characters	Applied before lexical matching while original text was retained for audit and manual review.	Reduces non-substantive variation without changing semantic content.
MATCHING UNIT AND WILDCARDS	normalised contiguous multi-word sequences; terminal wildcard indicated by an asterisk	Wildcards matched zero or more terminal alphanumeric characters; no unrestricted fuzzy semantic classification was used.	Captures morphological variants while preserving deterministic and reproducible matching.
OUTSIDE_TRANSPORT _SCOPE	Clear evidence that the publication concerned a non-transport disciplinary or application domain, without a substantive vehicle, mobility, road-network, or transport-infrastructure component.	Activated only when the incompatible context was explicit and no relevant transportation component could be established.	Strong exclusion condition.

The listed expressions represent the operational semantic categories used to support deterministic screening. Their activation was interpreted contextually rather than through isolated keyword occurrence, and the complete screening decision always depended on the combined evidence available within each bibliographic record.

The mere occurrence of the expression "floating car data" was not sufficient to establish eligibility. The available metadata had to demonstrate that the data performed a substantive analytical or methodological role in the study.

Records that did not meet a strong exclusion condition but for which positive eligibility could not be established with sufficient confidence were classified as uncertain. This category was deliberately used to minimise false-negative exclusions. In particular, records were not excluded because the abstract failed to report in detail the sensing configuration, sample characteristics, processing pipeline, validation approach, results, or operational implications. All uncertain records were retained for manual reassessment, and publications for which ambiguity persisted were advanced to full-text assessment rather than excluded.

2.6. Manual Adjudication and Decision Traceability

The deterministic framework was used to improve consistency and auditability but did not replace scientific judgement. Records activating exclusion conditions that required contextual interpretation were manually verified before a final decision was made. Manual reassessment was particularly important when the publication combined vehicle-derived and external data sources, when the abstract provided incomplete information regarding the actual role of FCD, when the distinction between an original study and a review-type contribution was unclear, or when related publications appeared to report overlapping research.

All records initially classified as uncertain were manually reassessed using the same substantive eligibility criteria applied throughout the review. Where title-and-abstract evidence remained inconclusive, the record was retained for full-text evaluation.

For each publication, the review database preserved the screening outcome, the activated inclusion or exclusion conditions, the expressions or contextual evidence supporting the decision, the principal exclusion reason where applicable, the result of manual adjudication, and any issue requiring verification at full-text level. This record-level documentation established an audit trail through which each screening decision could be reconstructed.

2.7. Full-Text Retrieval and Eligibility Assessment

The full texts of publications retained after title-and-abstract screening were sought through DOI links, publisher websites, Google Scholar, institutional repositories, subject repositories, and other legally accessible scholarly sources.

Reports that could not be obtained after these retrieval attempts were classified as reports not retrieved. They were not counted as relevance-based exclusions because their substantive eligibility could not be assessed.

Available full texts were evaluated against the same conceptual scope used during title-and-abstract screening, with particular attention to the actual role of FCD in the reported analysis. A publication was considered eligible when it employed core, enriched, or extended vehicle-derived FCD as an analytical input or central methodological object; addressed a transportation, mobility, logistics, safety, environmental, road-network, or infrastructure-related application; presented an identifiable original empirical or methodological contribution; and provided sufficient methodological information to establish its relevance to the objectives of the review.

Full-text exclusions were assigned when FCD were mentioned only as background or related work; when the data source fell outside the adopted operational definition and no relevant vehicle-derived component was present; when the transportation application was outside the review scope; when no identifiable original empirical or methodological contribution could be established; when the publication type was ineligible; or when the report substantially duplicated another eligible publication without providing additional data, methods, validation, or findings.

When more than one exclusion condition applied, a single primary reason was assigned according to the criterion that most directly rendered the report ineligible. This approach prevented double counting in the PRISMA flow diagram and ensured that the reported reasons remained mutually interpretable. For reporting and audit purposes, full-text exclusions were classified into eight mutually exclusive primary categories: FCD mentioned only as background or related work; exclusive reliance on external or non-vehicle-derived sensing; application outside the transportation or road-infrastructure scope; absence of an identifiable original empirical or methodological contribution; ineligible publication type; substantial overlap with another eligible report without complementary evidence; non-English full text; and exclusive analysis of non-motorised mobility without an analytically relevant motor-vehicle component.

Conference and journal publications addressing related research were not automatically treated as duplicates. They were compared with respect to the underlying dataset, study area, methodological procedure, experimental design, and reported results. Reports were consolidated only when they described substantially the same underlying study. In such cases, the most complete and methodologically informative publication was retained as the primary report, while companion publications were considered when they contributed additional or complementary evidence.

2.8. Data Extraction and Analytical Classification Framework

A structured data-extraction framework was applied to all eligible publications. As detailed in Table 6, the extracted variables covered bibliographic and contextual characteristics, FCD configuration, vehicle and sample characteristics, sensing and acquisition, operating conditions, preprocessing, analytical methods, validation and benchmarking, reported outcomes, deployment scale, transferability, infrastructure relevance, and study limitations.

Table 6. Data-extraction and analytical classification framework.

Analytical Dimension	Variables Extracted	Coding Rule	Purpose in the Synthesis
Bibliographic characteristics	Authors; title; publication year; source; DOI; publication type; database provenance.	Single value per report, except database provenance, which may be multiple.	Descriptive mapping and record traceability.
Study context	Country; city or region; network type; road class; urban, rural, highway, or mixed context.	Multiple geographical or network settings permitted.	Assessment of geographical coverage and operational context.
Research objective and application	Main objective; traffic state; travel time; mobility planning; logistics; safety; environmental assessment; infrastructure monitoring; other transport application.	One primary application assigned according to the dominant stated objective; secondary applications recorded where relevant.	Top-down classification by application domain.
FCD configuration	Terminology used; data provider; commercial, public, research, or proprietary source; core, enriched, or extended FCD.	Multiple source configurations permitted.	Characterisation of the evidence base and data-access models.
Vehicle and sample characteristics	Vehicle type; fleet composition; number of vehicles; trajectories; trips; observations; road segments; observation period.	Values retained as reported; missing information coded explicitly.	Assessment of scale, representativeness, and reproducibility.
Sensing and acquisition	GPS/GNSS; CAN; OBD; telematics; odometer; accelerometer; gyroscope; IMU; smartphone; black box; camera; complementary fixed or external sensors.	Non-mutually exclusive multiple coding.	Classification by sensing technology and identification of multi-sensor configurations.

Table 6. *Cont.*

Analytical Dimension	Variables Extracted	Coding Rule	Purpose in the Synthesis
Resolution and operating conditions	Sampling frequency; spatial resolution; speed; sensor placement; vehicle characteristics; weather or road conditions where relevant.	Multiple operating conditions recorded; not applicable allowed.	Assessment of comparability, signal quality, and transferability.
Preprocessing	Cleaning; filtering; outlier removal; interpolation; resampling; synchronisation; map matching; trajectory segmentation; normalisation; aggregation.	Non-mutually exclusive multiple coding.	Reconstruction of the analytical pipeline.
Analytical methods	Statistical inference; traffic modelling; time-series analysis; clustering; spatial analysis; signal processing; machine learning; deep learning; computer vision; data fusion.	Non-mutually exclusive multiple coding, with dominant approach identified where appropriate.	Classification by data-processing approach.
Validation and benchmarking	Reference sensors; profiler or pavement survey; loop detectors; ground truth; benchmark datasets; cross-validation; independent, cross-site, or real-world validation.	Multiple validation types permitted; absence recorded explicitly.	Assessment of evidential strength and methodological maturity.
Outcomes and performance	Reported indicators; errors; accuracy; precision; recall; correlation; robustness; uncertainty; principal findings.	Metrics retained in their original form; no forced conversion across incompatible measures.	Narrative comparison and identification of recurrent findings.
Deployment and transferability	Experimental or operational status; spatial and temporal scale; real-time capability; reproducibility; scalability; transferability across vehicles or sites.	Ordinal or narrative coding based on reported evidence.	Assessment of operational maturity.
Infrastructure relevance	Road roughness; surface anomaly; pothole; crack; distress; ride quality; IRI or proxy; maintenance planning; PMS integration.	Multiple infrastructure codes permitted.	Focused analysis of the underexplored pavement-monitoring dimension.
Limitations and research gaps	Author-reported limitations; calibration issues; heterogeneity; privacy; data access; standardisation; generalisability.	Multiple codes and narrative notes.	Cross-study synthesis of methodological and operational gaps.

The extraction framework was designed to connect the purpose of FCD use with the corresponding data sources, sensing configurations, analytical methods, validation strategies, and operational implications. Primary application domains were mutually exclusive, whereas sensing, processing, validation, and infrastructure-related variables could receive multiple codes within the same publication.

The eligible publications were organised through a top-down analytical framework comprising three principal dimensions: application domain, sensing technology, and data-processing approach. Each publication was assigned one primary application domain according to the dominant objective explicitly stated by the authors. Where a study addressed multiple objectives, the primary category reflected its principal research question and main reported outcome.

Sensing technologies, data sources, processing methods, validation approaches, and supplementary configurations were treated as non-mutually exclusive dimensions. A single publication could therefore receive multiple secondary codes when it combined heterogeneous sensors, data sources, or analytical techniques.

The classification framework was refined iteratively during data extraction to accommodate methodological configurations that were not fully represented in the initial taxonomy. Whenever a category was introduced, merged, or clarified, the revised definition was reapplied consistently to the entire eligible corpus.

All eligible publications contributed to the descriptive evidence mapping and cluster-level frequencies. A subset of representative publications was subsequently selected for detailed narrative discussion according to predefined illustrative criteria, including methodological recurrence, analytical distinctiveness, validation strength, operational scale, and relevance to the review objectives. This selection affected only the depth of discussion and did not influence eligibility or quantitative results.

2.9. Methodological and Reporting Appraisal

The reviewed literature encompassed heterogeneous observational, experimental, modelling, signal-processing, data-fusion, and machine-learning studies. Conventional intervention-oriented risk-of-bias instruments were therefore not considered appropriate for evaluating this evidence base.

Methodological and reporting completeness was appraised using the eight review-specific dimensions and operational definitions reported in Table 7.

Table 7. Methodological and reporting appraisal criteria.

Criterion	Fully Reported	Partially Reported	Not Reported	Not Applicable
Data source and analysed sample	Provider, source, sample unit, scale, and observation period described sufficiently to understand and potentially reproduce the analysis.	Source or sample described, but one or more material elements are incomplete.	No adequate description of source or sample.	Generally not applicable only in exceptional methodological studies without an empirical sample.
Sensing configuration and acquisition frequency	Sensor type, device or platform, relevant placement, and acquisition or sampling frequency fully reported.	Sensor or frequency reported only partially, or configuration lacks relevant detail.	Sensing configuration and acquisition frequency not reported.	Applicable only when no physical sensing configuration was involved.
Preprocessing and data cleaning	Filtering, cleaning, synchronisation, map matching, segmentation, normalisation, or equivalent pipeline sufficiently described.	Only selected preprocessing steps reported or key parameters omitted.	Preprocessing not described despite being relevant.	Not applicable when no preprocessing was required and this is justified.
Vehicle and operating conditions	Vehicle characteristics, sensor placement, speed, tyres, loading, driving conditions, or other relevant operational factors adequately reported.	Some relevant conditions reported, but material factors remain unspecified.	Relevant vehicle and operating conditions not reported.	Not applicable when these factors could not reasonably affect the study outcome.
Reference measurement, benchmark, or ground truth	Independent reference, benchmark dataset, profiler, survey, sensor, labelled data, or clearly defined ground truth available and described.	Reference present but limited, indirect, weakly described, or only internally derived.	No reference measurement, benchmark, or ground truth.	Not applicable for purely descriptive studies that do not claim predictive or measurement performance.
Quantitative performance or uncertainty metrics	Appropriate metrics and sufficient numerical results reported, including uncertainty where relevant.	Metrics reported incompletely or without sufficient detail for interpretation.	No quantitative performance or uncertainty measure reported where relevant.	Not applicable when quantitative performance was not an objective.
External or real-world validation	Independent dataset, cross-site test, external validation, or real-world operational evaluation reported.	Validation limited to internal resampling, a single site, or a non-independent dataset.	No validation beyond model development or calibration.	Not applicable only where validation is outside the legitimate scope of the study.
Deployment scale and transferability	Spatial and temporal scale, deployment setting, reproducibility, scalability, and transferability explicitly examined or demonstrated.	Scale reported but transferability or reproducibility only partly discussed.	Deployment scale or transferability not adequately addressed.	Not applicable for narrowly theoretical work, with justification.

The appraisal framework assessed methodological and reporting completeness rather than assigning an overall quality score or determining study eligibility. The four response categories were applied independently to each criterion in order to characterise strengths, limitations, and differences in reporting maturity across the included studies.

Each dimension was classified as fully reported, partially reported, not reported, or not applicable. The appraisal was used to characterise the transparency, robustness, validation maturity, and transferability of the available evidence. It was not used as an independent eligibility threshold, because excluding publications solely on the basis of incomplete reporting could have systematically removed exploratory contributions from emerging FCD application areas.

The appraisal framework was developed specifically for the present review and should be interpreted as a structured assessment of methodological and reporting completeness rather than as a validated risk-of-bias instrument.

2.10. Evidence Synthesis

All eligible publications contributed to the descriptive mapping of the literature. The synthesis combined quantitative frequency analysis with structured qualitative interpretation and considered publication year, geographical setting, application domain, sensing technology, processing method, validation strategy, and deployment scale.

Because sensing technologies, data sources, and processing approaches were coded as non-mutually exclusive, the corresponding frequencies were interpreted as the number of publications reporting each characteristic rather than as mutually exclusive percentages.

A narrative synthesis was used to examine the relationships among transportation objectives, sensing configurations, analytical pipelines, validation practices, and operational deployment. Particular attention was devoted to the contrast between mature traffic-oriented applications and comparatively less developed infrastructure-monitoring applications, especially those exploiting accelerometric or inertial vehicle data.

A statistical meta-analysis was not performed because the included studies differed substantially in their data sources, sampling frequencies, units of analysis, experimental conditions, outcome definitions, reference standards, and performance measures. These differences prevented the definition of sufficiently homogeneous effect measures and comparison groups.

All eligible publications were included in the evidence synthesis. Individual studies were cited as illustrative examples where they supported the interpretation of recurrent findings, methodological developments, validation practices, operational implementations, or research gaps. This narrative presentation did not involve any further eligibility assessment or reduction of the final evidence corpus.

2.11. Review Governance, Limitations, and Reproducibility

Title-and-abstract screening, full-text eligibility assessment, data extraction, and methodological appraisal were conducted by a single reviewer (S.S.). Formal inter-reviewer agreement could therefore not be calculated, and the absence of independent double screening is acknowledged as a methodological limitation. This may have introduced reviewer-dependent selection, extraction, or classification bias.

Several safeguards were adopted to reduce the potential influence of reviewer-dependent decisions. These included the use of predefined operational definitions and eligibility criteria, deterministic Boolean screening rules, conservative retention of uncertain records, manual reassessment of ambiguous decisions, assignment of a single primary exclusion reason to each ineligible publication, record-level documentation of the evidence supporting each decision, and consistent application of the full-text and classification criteria.

All bibliographic transformations, duplicate-resolution decisions, screening outcomes, full-text exclusion reasons, extracted variables, and methodological-appraisal results were retained in an auditable review database. The records preserved at each review stage and their reproducibility functions are summarised in Table 8.

To assess decision stability, a stratified sample of title-and-abstract and full-text decisions was reassessed by the same reviewer after completion of the primary screening phase.

Together, these materials permit reconstruction of the complete review process from the 2127 initially retrieved records to the final evidence corpus.

Table 8. Review audit trail and reproducibility records retained within the review database.

Review Stage	Records Retained	Reproducibility Function
Identification	Original Scopus and Google Scholar/Publish or Perish exports; source-specific identifiers; search dates; exact search expressions; record counts.	Reconstruction of the initial 2127-record evidence set and verification of source provenance.
Harmonisation and deduplication	Original and normalised bibliographic fields; DOI and title matches; duplicate-group identifier; retained master record; adjudication notes.	Verification of the removal of 566 duplicates and reconstruction of the 1561-record unique database.
Preliminary eligibility	Year, language, publication type, disciplinary eligibility, verification source, and exclusion reason.	Reconstruction of the transition from the deduplicated database to the 1183 records screened by title and abstract.
Title-and-abstract screening	Screening outcome; activated Boolean conditions; matched expressions; supporting title or abstract evidence; primary exclusion reason.	Record-level auditability of deterministic screening decisions.
Manual adjudication	Reason for review; contextual interpretation; final manual outcome; reviewer note; requirement for full-text verification.	Documentation of scientific judgement in ambiguous and uncertain cases.
Full-text retrieval	DOI or retrieval route; retrieval status; full-text availability; report-not-retrieved status.	Transparent separation of unavailable reports from relevance-based exclusions.
Full-text eligibility	Eligibility outcome; one primary exclusion reason; evidence supporting the decision; related-report assessment.	Reconstruction of the final study-selection process and PRISMA counts.
Data extraction and classification	All extracted variables; primary application; secondary technology and method codes; coding notes; missing-data status.	Reproducibility of quantitative mapping and narrative synthesis.
Methodological appraisal	Eight appraisal dimensions; category assigned; supporting evidence; not-applicable justification.	Verification of the assessment of methodological and reporting completeness.
Governance and version control	Framework version; dictionary version; date of execution or review; corrections and adjudication history.	Preservation of consistency and traceability across review iterations.

The audit trail preserved the evidence and decisions generated at each stage of the review, from bibliographic identification to methodological appraisal. This record-level documentation enabled reconstruction of the selection process, verification of the reported PRISMA counts, and traceability of both deterministic and manually adjudicated decisions.

3. Results

3.1. Study Selection and Corpus Characteristics

The study-selection process is summarised in the PRISMA flow diagram presented in Figure 1. Results are reported sequentially for bibliographic identification, duplicate removal, preliminary eligibility assessment, title-and-abstract screening, full-text retrieval, and final eligibility assessment. The composition of the review corpus resulted exclusively from application of the predefined eligibility criteria; no target number of publications, thematic quota, or predetermined sample size was established.

The searches conducted in Scopus and Google Scholar through Harzing's Publish or Perish retrieved 2127 bibliographic records, comprising 1161 records from Scopus and 966 records from Google Scholar. Following bibliographic harmonisation and cross-source duplicate resolution, 566 duplicate occurrences were removed, resulting in a deduplicated database of 1561 unique records.

A preliminary scoping search conducted in Scopus revealed a marked increase in the number of publications from approximately 2010 onwards. This trend was clearly observable in the annual distribution of the retrieved records and informed the decision to define the review period as extending from 2010 to 2025. Figure 2 presents the annual number of records identified during this preliminary scoping analysis.

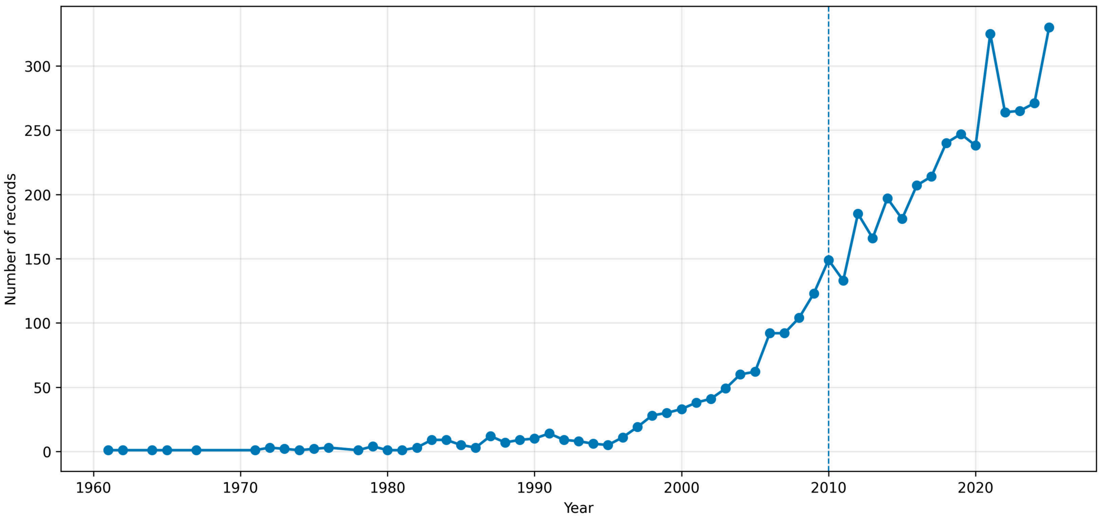

Figure 2. Annual distribution of about 4000 records identified in the preliminary Scopus scoping search used to support the definition of the review period. The dashed line indicates the lower temporal boundary adopted for the systematic review.

The annual distribution should be interpreted as a description of the retrieved search output rather than as a direct estimate of the temporal prevalence of eligible FCD research. At this stage, the dataset still contained records that were subsequently removed because they did not satisfy the publication-period, language, publication-type, disciplinary, or substantive eligibility criteria.

Following duplicate removal and preliminary bibliographic eligibility assessment, 1183 records entered title-and-abstract screening.

During title-and-abstract screening, 530 records were classified as potentially eligible, 183 were classified as uncertain, and 470 were excluded directly at title-and-abstract level. Manual reassessment of the uncertain records resulted in the retention of 123 additional records and the exclusion of 60 records. Overall, 530 records were excluded during title-and-abstract screening, while 653 reports were retained for full-text retrieval and eligibility assessment.

Geographical assignment was based on the empirical study area or, where appropriate, on the location of the analysed dataset, and not on authors' affiliations. The distribution should therefore be interpreted as a descriptive map of the available evidence base, not as a geographical sampling target (Figure 3).

Of the 653 reports sought for retrieval, 578 full texts were successfully obtained, corresponding to 88.51% of the reports sought. The remaining 75 reports could not be retrieved after the documented searches of DOI landing pages, publisher websites, Google Scholar, institutional repositories, and other legally accessible scholarly sources. Reports that could not be retrieved were recorded separately and were not treated as relevance-based exclusions because their substantive eligibility could not be assessed.

The 578 retrieved reports were assessed against the full-text eligibility criteria and 413 reports were excluded following full-text assessment, with one mutually exclusive primary reason assigned to each report. FCD were mentioned only as background or related work and were not used substantively in the reported analysis in 118 reports. A further 82 reports relied exclusively on external or non-vehicle-derived sensing without a substantive vehicle-derived component, while 53 addressed applications outside the transportation or road-infrastructure scope. No identifiable original empirical or methodological contribution was found in 48 reports, and 41 reports corresponded to ineligible publication types. Thirty-two reports substantially overlapped with another eligible publication without providing complementary data, methods, validation, or findings. Twenty-one reports were excluded because the full text was not written in English, and eighteen concerned exclusively non-motorised mobility without an analytically relevant motor-vehicle component.

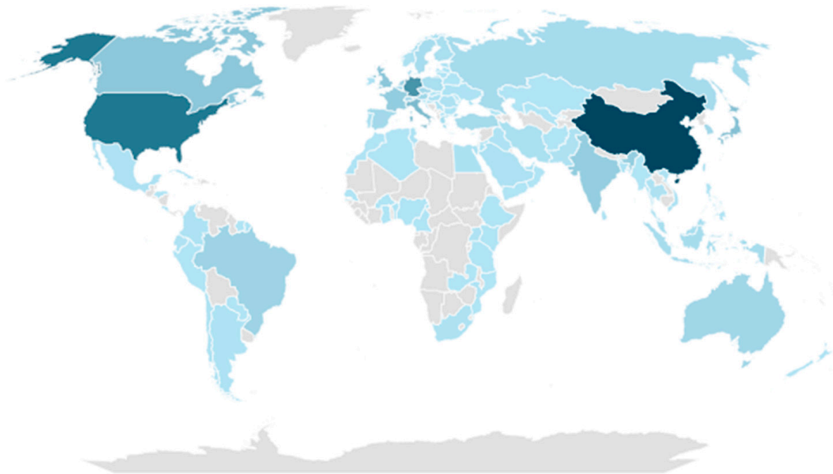

Figure 3. Geographical distribution of the empirical study settings reported in the included publications. The colour scale ranges from darker shades, indicating a higher number of records, to light grey, indicating no records. The macro-regional distribution was as follows: Europe, 59 publications; Asia, 61; North America, 26; Latin America, 5; Africa, 4; Oceania, 2; multiple regions, 8.

The remaining 165 publications formed the evidence-mapping corpus. This number resulted from the application of the predefined eligibility criteria and was not determined through purposive sampling, thematic balancing, or a predetermined target corpus size.

Table 9 provides a quantitative mapping of the 165 eligible publications across the principal analytical dimensions considered in the review. Primary application domains were coded as mutually exclusive, whereas sensing technologies, data sources, and validation approaches could receive multiple codes within the same publication. Accordingly, percentages for non-mutually exclusive dimensions may exceed 100% when summed.

Table 9. Quantitative mapping of the 165 publications included in the review.

Analytical Dimension	Category	Nr.	%
Primary application domain	Travel and traffic-state estimation	66	40.0
	Mobility patterns and transport planning	34	20.6
	Freight and logistics	12	7.3
	Driving behaviour and road safety	21	12.7
	Environmental and energy assessment	12	7.3
	Infrastructure monitoring	20	12.1
Sensing technology	GPS/GNSS	128	77.6
	CAN, OBD or vehicle telemetry	34	20.6
	Accelerometer, gyroscope or IMU	29	17.6
	Smartphone-based sensing	18	10.9
	Black box or dedicated onboard sensing	14	8.5
	Vehicle-mounted camera	11	6.7
Data-processing approach	Statistical or traffic modelling	82	49.7
	Map matching and trajectory processing	67	40.6
	Machine learning	52	31.5
	Spatial analysis or clustering	49	29.7
	Data fusion	41	24.8
	Time-series modelling or forecasting	38	23.0
	Signal processing	31	18.8
	Deep learning or computer vision	28	17.0

Table 9. *Cont.*

Analytical Dimension	Category	Nr.	%
Complementary data source	Fixed detector or inductive loop	31	18.8
	Roadside radar or stationary camera	17	10.3
	Bluetooth, ETC or communication data	22	13.3
	Other contextual or external source	39	23.6
Validation approach	Independent reference or ground truth	54	32.7
	Internal or cross-validation	47	28.5
	Cross-site or external validation	18	10.9
	No explicit validation reported	63	38.2
Geographical region	Europe	59	35.8
	Asia	61	37.0
	North America	26	15.8
	Latin America	5	3.0
	Africa	4	2.4
	Oceania	2	1.2
	Multiple regions or not reported	8	4.8
Deployment scale	Experimental or single-site	74	44.8
	Urban or network-level	52	31.5
	Regional, national or multi-site	24	14.5
	Operational or real-time deployment	15	9.1
PMS integration level	No explicit PMS connection	137	83.0
	Potential or indirect maintenance relevance	19	11.5
	Explicit PMS-oriented integration	9	5.5

Application domain, geographical region, deployment scale, and PMS integration level are mutually exclusive. Sensing technology, data-processing approach, complementary data source, and validation approach are non-mutually exclusive; therefore, percentages within these dimensions may sum to more than 100%.

The eligible publications were subsequently organised into a stable set of application, sensing, and data-processing clusters. The classification structure was progressively refined as recurrent methodological configurations emerged and was subsequently applied consistently across the complete eligible corpus.

All 165 eligible publications contributed to the descriptive evidence mapping and to the calculation of cluster-level frequencies. Within this corpus, a representative subset of publications was selected for detailed narrative discussion. These studies were chosen to illustrate recurrent methodological configurations, distinctive analytical developments, robust validation strategies, large-scale or operational implementations, and research gaps relevant to the objectives of the review.

The selection of representative publications affected only the depth of narrative discussion. It did not influence study eligibility, cluster assignment, quantitative frequencies, or the composition of the final evidence corpus.

3.2. Classification Framework and Analytical Dimensions

The selected studies were organized according to a top-down classification framework linking the overarching purpose of FCD use to the underlying technical components. Three analytical dimensions were considered: (i) application domain, (ii) sensing technology, and (iii) data processing approach. This structure was adopted to examine the relationships between transportation objectives, data-acquisition systems, and the analytical methodologies used to transform vehicle-derived observations into operational information.

This structure was chosen not simply to follow previous application-based taxonomies, but to refine and extend them. Existing large-scale reviews typically cluster FCD research into domains such as traffic state estimation, traffic safety, and route planning. While this approach effectively captures dominant research trends, it also tends to mask infrastructure-related applications, which often remain embedded within traffic-centric analyses rather than being treated as a distinct thematic area [3]. As a result, applications involving pavement condition monitoring or infrastructure assessment are not explicitly recognized, even though they rely on specific sensing modalities and processing strategies that may differ substantially from those used in traditional mobility-oriented studies.

By reorganizing the selected literature through a top-down framework that begins with application domains and explicitly incorporates infrastructure-oriented uses, the proposed classification addresses some of the limitations of earlier application-based taxonomies. Each application domain is subsequently linked to the sensing technologies and data processing approaches adopted in the corresponding studies. This structure supports the identification of methodological relationships, gaps, and research opportunities that may remain less visible in predominantly traffic-oriented classifications. The framework therefore provides a structured representation of the range of FCD applications and methodological configurations included in the selected corpus (Figure 4).

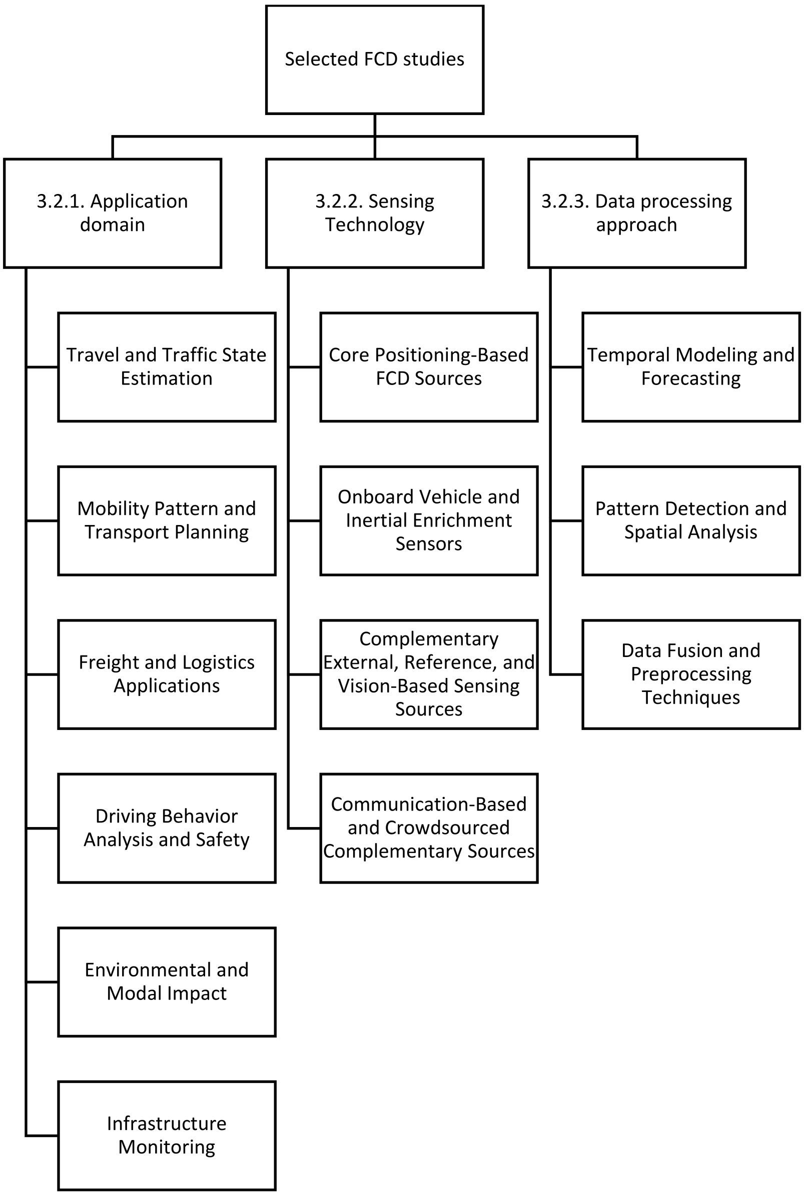

Figure 4. Block diagram illustrating the classification framework adopted for the selected corpus. The included publications were organized according to application domain, sensing technology, and data processing approach, supporting the comparison of methodological configurations and the identification of recurrent patterns and comparatively underrepresented areas within the analysed corpus.

Figure 4 provides a conceptual overview of the classification framework and its relationship with the survey's main thematic sections.

The application domain describes the primary purpose for which FCD were employed. Each of the 165 eligible publications was assigned one primary application domain according to its dominant research objective. As the first layer of the framework, the application domain also shapes the sensing requirements and data characteristics for each use case.

The sensing technology dimension (ii) refers to the type of data acquisition systems employed in each study, ranging from GPS and multi-constellation Global Navigation Satellite Systems (GNSS) positioning to smartphone-based accelerometers, onboard inertial sensors, vehicle telemetry systems, and camera-derived observations. The choice of sensing modality is inherently influenced by the target application, since different objectives require different spatial, temporal, or dynamic measurement capabilities. In turn, the properties of the sensing technologies constrain the analytical methods that can be applied in downstream processing.

The data processing dimension (iii) captures the analytical methods used to transform raw trajectories or sensor signals into operational indicators. These methods include data filtering and cleaning procedures, map-matching techniques, trajectory segmentation, clustering algorithms, statistical inference models, machine learning approaches, smoothing and interpolation techniques, and multi-source data fusion strategies. As the final layer of the framework, data processing depends on both the application domain and the employed sensing technologies, since different sensor-objective combinations require tailored analytical pipelines. Overall, the studies included in the selected corpus demonstrate substantial methodological sophistication in addressing noise, data sparsity, and heterogeneity, although advanced processing techniques were not evenly represented across the analysed application domains.

In the following subsections, each of these three analytical dimensions is addressed in greater depth, first through a general overview and subsequently through a more detailed examination of the aspects that characterize the corresponding body of literature.

3.2.1. Classification by Application Domain

From a general perspective, the application of FCD has progressively expanded beyond basic traffic monitoring to encompass a broad range of operational and strategic uses in transport and mobility analysis. The reviewed literature shows that FCD are applied to real-time traffic state estimation, travel time and speed analysis, route optimization, emission and energy assessment, road safety evaluation, and, in a more limited number of cases, infrastructure condition monitoring. This diversity reflects the flexibility of FCD as a data source and its adaptability across heterogeneous analytical contexts.

The classification by application domain provides a structured overview of how FCD are leveraged across these use cases and enables a comparative assessment of their relative maturity. Traffic-state estimation and mobility-planning applications accounted for 100 of the 165 eligible publications (60.6%), confirming the predominance of traffic and mobility-oriented research within the reviewed corpus. Infrastructure monitoring represented the primary application domain in 20 of the 165 eligible publications (12.1%), indicating a substantially smaller evidence base than that observed for traffic-state estimation and mobility planning. This confirms the marginal role of infrastructure-focused applications within the current FCD literature and highlights an imbalance in research attention that is relevant for assessing the state of the art and identifying underexplored directions for future research.

Beyond illustrating the prevalence of traffic- and mobility-oriented applications, Table 10 summarizes, for each application domain, the main data sources, methods, key results, and operational implications reported in the reviewed studies. Traffic-related applications, including travel time and speed estimation, congestion monitoring, and route prediction, primarily rely on positioning-based FCD derived from GNSS, often complemented by fixed sensors such as loop detectors and Electronic Toll Collection (ETC) systems. This integration enables continuous network-wide coverage while preserving local accuracy, leading to improved traffic prediction capabilities and more effective signal control strategies. Fixed detectors or inductive loops were used as complementary sources in 31 publications (18.8%), roadside radar or stationary cameras in 17 publications (10.3%), and Bluetooth, ETC, or communication data in 22 publications (13.3%).

Table 10. Classification of FCD applications by use.

Category	Data	Methods	Results	Main Implications	References
Travel and Traffic State Estimation	FCD, sensors, simulation	Data fusion, traffic models, Machine Learning (ML)	Improved travel time accuracy; congestion mapping	Network-wide traffic monitoring and ITS decision support	[8–28]
Mobility Pattern and Transport Planning	FCD, land-use data, Points of Interest (POIs)	Clustering, indicators, spatial analysis	Fine-grained mobility and accessibility patterns	Evidence-based planning and zoning decisions	[29–46]
Freight and Logistics Applications	FCD, freight surveys	Robust routing, demand modelling	Higher delivery reliability under uncertainty	Sustainable urban freight planning	[47–53]
Driving Behavior Analysis and Safety	Low-frequency FCD, road geometry	CNNs, speed–safety analysis	Lane detection > 90%; safety hotspots	Data-driven road safety screening	[54–67]
Environmental and Modal Impact	FCD, EV tests, user surveys	VSP models, literature synthesis	Improved EV energy models; mode shift evidence	Sustainable mobility policy design	[28,68–75]
Infrastructure Monitoring	Inertial sensors, black-box data	Odometry, roughness indices	Reliable International Roughness Index (IRI) proxies; scalable screening	Low-cost network-level asset management	[76–84]

The classification is based on the primary application domain identified in each reviewed study. Several contributions span multiple categories; in such cases, studies were assigned to the dominant use reported by the authors.

Applications related to mobility pattern analysis and transport planning typically integrate FCD with contextual and crowdsourced datasets, such as urban morphology information, mobile network data, and Bluetooth detections. The fusion of trajectory data with spatial and socio-technical context supports spatiotemporal mobility analysis and demand-responsive public transport planning, contributing to more effective zoning strategies and adaptive mobility policies. In the freight and logistics domain, FCD are commonly combined with origin–destination matrices, traffic counts, and stakeholder-provided information, reflecting the operational complexity of freight systems and enabling route optimization under time-dependent conditions, with associated efficiency gains and cost reductions in urban logistics.

Studies focusing on driving behaviour and road safety exploit FCD alongside road geometry, historical crash databases, and vehicle internal data accessed through Controller Area Network (CAN) bus systems. This integration allows the identification of speeding patterns, unsafe manoeuvres, and safety-critical locations, directly supporting targeted risk mitigation and safety interventions. Environmental and modal impact assessments further extend FCD applications by combining speed and acceleration profiles with power-based models and environmental data to estimate emissions and energy consumption, providing quantitative support for sustainability-oriented transport policies.

Infrastructure monitoring represents a distinct yet comparatively underrepresented application domain. Unlike traffic-oriented uses, it mainly relies on accelerometers, vibration sensors, and onboard diagnostic data that are sensitive to road surface irregularities. While these approaches offer clear benefits, such as early damage detection and cost-effective maintenance planning, their limited presence in the literature highlights the substantial potential for expanding FCD-based methodologies beyond mobility analysis toward more systematic and large-scale infrastructure monitoring applications.

From a more specific perspective, the use of FCD has progressively expanded from basic traffic monitoring toward a wide range of operational and strategic applications in transport and mobility management. One of the most established domains concerns travel time and speed estimation on urban [20] and highway networks, where data collected from probe vehicles are used to model traffic conditions and predict delays. Studies such as [25] show that estimation accuracy improves when FCD are combined with fixed sensors, including loop detectors and ETC systems, through models that decompose travel time into acceleration, cruising, and deceleration phases, achieving average errors below 5% under congested conditions and between 10% and 20% in lighter traffic. Simulation-based investigations further confirm the robustness of FCD-derived speed metrics across entire road segments, even at penetration rates as low as 5% on high-volume roads, supporting traffic state estimation when dense sensor infrastructures are unavailable [26].

FCD have also been extensively applied to congestion monitoring and network performance assessment at the urban scale, as shown in studies conducted in cities such as the metropolitan areas in China [27], where congestion maps and speed profiles were derived from taxi-based GPS data. Beyond traffic performance, FCD have been employed to analyze vehicle energy consumption by linking speed and acceleration profiles to power-based models, highlighting higher energy demand under stop-and-go conditions typical of urban roads [68]. Predictive applications have also emerged, with deep learning models such as Long Short-Term Memory (LSTM) and Generative Adversarial Networks (GANs) trained on FCD to forecast vehicle trajectories and future routes, supporting route planning and mobility management [28].

At broader spatial and temporal scales, FCD enable the investigation of mobility patterns and transport planning by uncovering spatiotemporal congestion structures and accessibility dynamics, as demonstrated using taxi data in Wuhan (China) [29] and large-scale private vehicle datasets in Italian cities such as Brescia, Catania, and Salerno [42]. These approaches support origin–destination reconstruction, traffic zoning, and demand-responsive planning, including public transport optimization in tourist-intensive contexts [43]. Additional applications relate to smart mobility and ITS strategies, where FCD integrated with vehicle diagnostics have been used to assess operational measures and eco-driving impacts [44,45].

In the freight and logistics domain, FCD have been used for freight modelling and the design of urban logistics scenarios, including route optimization under time-dependent and stochastic travel conditions and the development of Sustainable Urban Logistics Plans (SULPs) [47,48]. Driving behavior and road safety represent another relevant area, where FCD have been exploited to infer safety-related patterns by linking trajectories with road features and behavioral indicators [54], and to support lane-level inference tasks such as lane number mining from low-frequency trajectories using deep learning [55].

In addition to traffic-oriented applications, several studies exploit vehicle-borne sensing that can be interpreted within an FCD-like paradigm, especially when data are collected from circulating vehicles through smartphone sensors, black boxes, or onboard inertial units.

A consolidated line of research relies on smartphone accelerometers coupled with GNSS/GPS to estimate road roughness and ride quality under real driving conditions [85–88], with later works extending these approaches through machine learning and signal processing pipelines for road quality classification and anomaly/distress identification [89–97]. Crowdsourcing configurations further emphasize scalability by aggregating observations from multiple users or probe vehicles [98–103].

A complementary stream of contributions uses black boxes and vehicle-mounted inertial sensing embedded in operational fleets, showing that vertical acceleration data can support the detection of abnormal pavement conditions and maintenance-oriented analytics [81,100,104–106]. However, these studies are often constrained to specific fleets, controlled setups, or single-sensor configurations, and they are rarely aggregated within large, heterogeneous fleet-based frameworks.

Despite this wide range of mature applications, infrastructure monitoring remains marginal within the FCD literature. Only isolated contributions exploit in-vehicle inertial sensing (e.g., wheel-mounted accelerometers) in ways that could be extended toward road-surface assessment, but these studies remain limited in scale, sensor diversity, and integration with fleet-based FCD frameworks [78,84]. Similarly, only limited evidence exists on multi-sensor fusion combining inertial measurements and vision-based observations for pavement assessment [107–110], suggesting that integrated, scalable pipelines remain largely underdeveloped. Overall, the literature offers a broad, diverse set of contributions on vehicle-based sensing for pavement and road surface assessment. Many studies successfully demonstrate the feasibility of extracting infrastructure-related indicators from onboard data, particularly by accelerometers or vision-based sensors considered independently. These works have contributed to important methodological insights and validated the sensitivity of specific sensing modalities to surface irregularities under real driving conditions.

At the same time, a significant portion of the existing research relies on single sensor configurations or on ad hoc measurement campaigns conducted with specially instrumented vehicles or dedicated sensing platforms. While these approaches allow controlled data acquisition and detailed analysis, their applicability is often confined to limited spatial extents, specific vehicle types, or short observation periods. Fewer studies investigate the joint exploitation of heterogeneous sensor modalities, such as inertial measurements, vision-based observations, positioning data, and contextual information collected from circulating vehicle fleets. When multi-sensor approaches are considered, they are typically evaluated on small-scale datasets and remain weakly integrated into large fleet-based FCD frameworks.

The reviewed application domains also reveal significant differences in operational maturity and deployment scalability. Traffic-oriented applications, such as travel time estimation, congestion monitoring, and mobility analytics, generally benefit from large-scale datasets, standardized processing pipelines, and relatively robust validation practices. In contrast, infrastructure-oriented applications remain more fragmented and frequently rely on small-scale experimental campaigns or single-sensor configurations. While accelerometer-based approaches offer clear advantages in terms of low-cost deployment and continuous monitoring potential, their performance is often influenced by vehicle type, speed, tire characteristics, sensor placement, and driving behaviour. Furthermore, many studies provide limited discussion of calibration procedures, long-term robustness, or transferability across heterogeneous fleets and operating conditions, which currently constrains the operational integration of accelerometric FCD into large-scale PMS frameworks.

To summarise, these observations suggest several open research gaps for infrastructure monitoring within the FCD paradigm. In particular, standardized and transferable methodologies for aggregating and normalizing accelerometric signals across heterogeneous vehicles and operating conditions are still limited. Evidence on robust multi sensor fusion strategies that can enhance reliability and reduce sensitivity to vehicle specific effects remains scarce. Furthermore, large-scale validation studies linking FCD-derived pavement indicators to reference measurements and supporting their systematic integration into PMS are relatively few. Overall, despite the increasing availability of onboard sensing technologies, the full potential of accelerometer-enriched FCD for continuous, network-wide pavement condition monitoring has yet to be fully realized.

3.2.2. Classification by Sensing and Data-Source Role

From a general perspective, the technological landscape supporting the collection and processing of FCD has evolved substantially, driven by the increasing availability and integration of heterogeneous sensing technologies (Table 11). Beyond describing this evolution, Table 11 summarizes the main sensing and data-source role categories adopted in the reviewed studies, reporting for each category the typical data streams, processing methods, key results, and main implications.

Table 11. Classification of sensing and data-source roles in FCD-related studies.

Category	Data	Methods	Results	Main Implications	References
Core Positioning-Based FCD Sources	GNSS (GPS, GLONASS, Galileo, BeiDou), ETC	Map-matching; trajectory reconstruction; travel time and speed estimation	Wide spatial coverage; reduced accuracy in dense urban environments	Core FCD source; integration with complementary sensors required	[1,22–25,28,111–114]
Onboard Vehicle and Inertial Enrichment Sensors	CAN bus, odometer, accelerometer, magnetometer	Vehicle dynamics analysis; roughness and safety detection	High-resolution motion data; vehicle-dependent signals	Rich information content; calibration and normalization required	[81,84,85,87,89–94,97,100,105,115–122]
Complementary External, Reference, and Vision-Based Sensing Sources *	Inductive loops, radar, camera-based systems	Traffic flow and speed measurement; signal control; incident detection	High local accuracy; limited spatial coverage	Accurate local reference; limited scalability	[107–109,123–142]
Communication-Based and Crowdsourced Complementary Sources	Bluetooth travel time re-identification; V2I communications (GPRS/UMTS); extended FCD (GPS + CAN + vision); mobile probes	Travel time interpolation (LSTM); trajectory weighting; multi-sensor fusion; anomaly detection	Improved travel time estimation; enhanced traffic load representation; variable spatial resolution	Scalable and cost-efficient coverage; privacy-sensitive; accuracy dependent on penetration rate and detector spacing	[143–147]

The classification is based on the primary technology identified in each reviewed study. Several contributions span multiple categories; in such cases, studies were assigned to the dominant use reported by the authors. * This category includes external, reference, and vision-based sources used to support, calibrate, validate, benchmark, or extend FCD-related analyses. These sources were not treated as independent core FCD-generating technologies unless they were acquired from moving vehicles and linked to georeferenced trajectories.

Satellite positioning systems, including the GPS and multi-constellation GNSS solutions, constitute the foundational technology for FCD acquisition and are primarily used for vehicle localisation, trajectory reconstruction, and travel time estimation. Their widespread adoption is supported by wide spatial coverage, high temporal resolution, and low deployment costs; however, positioning accuracy may degrade due to signal obstruction and multipath effects, particularly in dense urban environments, motivating integration with complementary sensors. GPS or GNSS data were reported in 128 of the 165 eligible publications (77.6%), making satellite positioning the most frequently identified sensing technology.

Vehicle internal sensors and onboard systems, such as CAN bus data, odometers, accelerometers, and magnetometers, provide detailed, environment-independent information on vehicle dynamics. These data support driving behaviour analysis, safety assessment, and, in selected cases, road condition detection, but require sensor-specific calibration and are inherently limited to periods and locations where vehicles are present. Accelerometers, gyroscopes, or inertial measurement units were reported in 29 publications (17.6%).

Smartphone-based configurations were identified in 18 studies (10.9%), while black-box or dedicated onboard sensing systems were reported in 14 studies (8.5%).

Complementary external and reference sources—including fixed detectors, roadside radar, stationary cameras, inductive loops, and camera-based systems—are mainly employed for traffic flow measurement, signal control, and anomaly detection at specific locations. While offering high accuracy and a valuable reference for calibration and validation of FCD-derived indicators, their high installation and maintenance costs and limited spatial coverage restrict scalability. Vehicle-mounted cameras were identified in 11 publications (6.7%).

Communication-based and crowdsourced data sources, such as mobile phone positioning data and Bluetooth (BT) sensors, complement traditional FCD by enabling large-scale, cost-effective data collection with high penetration rates. These technologies are commonly used for crowdsourced speed estimation and origin–destination analysis, while posing challenges related to privacy protection, inconsistent sampling rates, and dependence on user devices.

Overall, the classification by technology highlights that contemporary FCD ecosystems rely on the complementary integration of heterogeneous sensing solutions, with each technology contributing distinct strengths and limitations that directly affect achievable applications, data quality, and system scalability.

From a more specific perspective, contemporary FCD ecosystems rely on an integrated combination of satellite-based positioning systems, in-vehicle sensors, roadside infrastructure, and communication-based data sources, each contributing complementary information to enhance accuracy, robustness, and spatiotemporal coverage. Satellite positioning systems, particularly GPS, remain the most widely adopted technology for FCD acquisition and enable high-resolution trajectory reconstruction; however, their performance is affected by multipath effects, signal obstruction, and environmental conditions, resulting in positioning errors ranging from 5 to 30 m in dense urban environments [112]. To address these limitations, advanced filtering and map reconstruction techniques, including Gaussian modeling and Otsu-based algorithms, have been proposed [112], while optimized sampling strategies indicate that acquisition intervals of 1–3 s provide an effective trade-off between accuracy and data volume [113]. The adoption of multi-constellation GNSS solutions, integrating systems such as Global Navigation Satellite System (GLONASS), Galileo, and BeiDou, further improves signal availability and positioning reliability in complex urban settings [114], particularly when combined with digital maps and wireless communication technologies [1]. GNSS data have also been successfully integrated with artificial intelligence models [148] to support trajectory prediction in complex routing scenarios [28]. Additional positioning-related data sources, such as ETC systems, have been shown to enhance urban travel time estimation when combined with FCD and fixed sensor data, even under congested traffic conditions [25]. Beyond positioning technologies, in-vehicle sensing systems play a crucial role in enriching FCD. The CAN Bus enables high-frequency access to vehicle dynamics data and has demonstrated improved performance, robustness, and integration capabilities in hybrid vehicle platforms compared to legacy systems [118]. Odometers and wheel-mounted accelerometers have been employed to estimate traveled distance with greater accuracy than traditional approaches, particularly in environments with weak GPS coverage [84]. Magnetometers provide an additional sensing modality by detecting vehicle-induced disturbances in the Earth's magnetic field and have been integrated with FCD to analyze traffic-related noise and environmental impacts [119]. Complementary information is provided by roadside and fixed infrastructure sensors, including radar, cameras, and inductive loop detectors, which provide continuous, high-precision measurements at specific locations. The integration of these fixed sensors with FCD has been shown to enhance speed estimation accuracy and traffic state assessment [130], as well as to support more efficient traffic signal control strategies [131]. Roadside radar sensors contribute detailed speed measurements that, when combined with FCD, facilitate the identification of abnormal driving patterns on rural networks [132], while data-driven methods (e.g., Self-Organizing Maps (SOM)) have been used to characterize intersection-level dynamics [123]. Inductive loop detectors, despite their spatial limitations, remain valuable for calibration and validation purposes when fused with FCD [124]. Finally, communication-based and crowd-sourced data sources, such as mobile network positioning and Bluetooth sensing, provide additional layers of traffic information. Mobile phone data, when combined with Bluetooth and FCD, have been shown to improve travel time and speed estimation accuracy [146], while Bluetooth/Vehicle-to-Infrastructure (V2I)-based data collection can complement FCD for enhanced traffic monitoring [147].

In addition to conventional positioning and communication technologies, a substantial body of FCD-related research exploits vehicle-borne inertial sensing, often implemented through low-cost or consumer-grade devices. Smartphone-based platforms that integrate accelerometers, gyroscopes, and GPS represent one of the most widely adopted solutions due to their scalability and ease of deployment. These systems have been used for road roughness estimation, pavement condition classification, and anomaly detection through vibration-based analytics [85,87,89,90,92–94]. Depending on the application, sensing configurations range from accelerometer-only setups [91,97,113] to multi-sensor inertial measurement units combining accelerometers and gyroscopes [90,94,115,121], often embedded in smartphones or connected to On-Board Diagnostics (OBD) devices [89,122].Beyond smartphones, dedicated vehicle-mounted inertial sensors and black boxes provide higher sampling rates and improved stability, enabling more robust pavement monitoring under operational conditions. Vertical acceleration data acquired from black boxes and onboard accelerometers have been successfully used for roughness evaluation and anomaly detection [81,100,116], while calibration strategies leveraging overlapping measurements across multiple vehicles enhance spatial consistency and localization accuracy [105]. In connected and automated vehicle contexts, inertial sensing is further enriched through Original Equipment Manufacturer (OEM) onboard sensors and Vehicle-to-Vehicle (V2V)/V2I communications, supporting large-scale, fleet-based pavement condition assessment [117].

A complementary sensing dimension within FCD ecosystems is provided by vision-based technologies, which enable direct observation of pavement surface conditions. Vehicle-mounted, action, and smartphone cameras have been widely adopted to capture pavement imagery under real traffic conditions, supporting crack detection, distress classification, and surface quality assessment [125,126,133,134]. Early implementations rely on conventional computer vision pipelines, whereas more recent systems predominantly exploit deep learning architectures, including Convolutional Neural Networks, CNN-based detectors, encoder–decoder segmentation networks, and You Only Look Once (YOLO)-based real-time frameworks [127,135–137]. Transformer-based models and hybrid CNN–transformer architectures further enhance feature representation and robustness across varying illumination and surface conditions [128,129,138–140].

Vision sensing is increasingly integrated with other onboard data sources to improve reliability and contextual awareness. Multi-modal configurations combine cameras with accelerometers, gyroscopes, and GNSS to enable synchronized acquisition and cross-validation of pavement anomalies [107–109,141]. Additional sensing modalities, such as RGB-D cameras [142], extend the applicability of vision-based monitoring beyond ground vehicles, supporting detailed distress detection and quantification over larger spatial scales.

From a comparative perspective, no sensing technology currently satisfies all operational requirements simultaneously. GNSS-based systems provide scalable and cost-efficient spatial coverage, but their positioning accuracy may degrade under complex urban conditions. Smartphone-based sensing platforms are highly scalable and economically accessible, yet they remain sensitive to mounting conditions, device heterogeneity, and vehicle-specific dynamics. Dedicated onboard sensors and black-box systems generally provide higher signal quality and improved robustness, although they often require controlled calibration procedures and access to proprietary vehicle data. Vision-based technologies enable direct pavement distress recognition with increasingly high detection accuracy; however, their performance may be affected by lighting conditions, weather variability, occlusions, and computational requirements. These trade-offs suggest that future large-scale infrastructure monitoring frameworks will likely depend on multi-sensor integration strategies capable of balancing scalability, robustness, and operational reliability.

To summarise, the classification by sensing technology highlights that contemporary FCD ecosystems are inherently multi-sensor and rely on the complementary integration of heterogeneous data sources rather than on a single dominant technology. Satellite-based positioning systems provide the backbone for large-scale trajectory reconstruction and mobility analysis, while in-vehicle inertial and telemetry sensors enrich FCD with high-frequency information on vehicle dynamics that is potentially sensitive to infrastructure-related phenomena. Roadside sensors and fixed infrastructure remain essential for localized, high-accuracy measurements and validation, whereas communication-based and crowdsourced data sources enable scalable, cost-effective coverage at the network level. Vision-based technologies further extend FCD capabilities by enabling direct observation of pavement surface conditions, particularly when integrated with inertial and positioning data. Overall, this classification underscores that the analytical potential of FCD is strongly conditioned by sensing heterogeneity and data fusion strategies, and that the effective exploitation of FCD for infrastructure monitoring depends on the coordinated use of multiple sensing modalities rather than on isolated data streams.

3.2.3. Classification by Data Processing

From a general perspective, the processing of Floating Car Data (FCD) can be structured into a set of methodological approaches describing how raw trajectories and sensor signals are transformed, modelled, and integrated to extract meaningful information, independently of the final application domain (Table 12). Beyond providing a methodological overview, Table 12 groups the reviewed studies by dominant processing approach and summarizes, for each category, the typical input data, methods, key results, and main implications.

Table 12. Classification of FCD applications by data processing.

Category	Data	Methods	Results	Main Implications	References
Temporal Modeling and Forecasting	FCD time series, loop detectors, calendar data	LSTM; ARIMA; Support Vector Regression; Tucker decomposition	Accurate travel time and trajectory prediction; robustness under sparse data	Short-term forecasting and missing-data imputation	[23,25,149–154]
Pattern Detection and Spatial Analysis	FCD, taxi GPS data, environmental context	Self-Organizing Maps; Kernel Density Estimation; GANs; LSTM; Vehicle Specific Power regression	Identification of traffic hotspots and behavioural patterns	Network diagnostics and policy-oriented analysis	[28,29,46,55,123,155,156]
Data Fusion and Preprocessing Techniques (including vision-based methods)	FCD, Bluetooth data, loop detectors, images	Adaptive Smoothing Method; Phase-Based Smoothing; DBSCAN; CNN (LeNet-5)	Improved accuracy and structural robustness	Scalable integration of heterogeneous data sources	[55,68,81,86–91,94,97,106,107,109,115–117,124–129,157–168]

The classification is based on the primary data processing approach identified in each reviewed study. Several contributions span multiple categories; in such cases, studies were assigned to the dominant use reported by the authors.

Temporal modelling and forecasting techniques—including LSTM networks, AutoRegressive Integrated Moving Average (ARIMA) models, Support Vector Regression (SVR), and tensor-based approaches such as Tucker decomposition—are mainly applied to time-dependent tasks such as travel time prediction, trajectory forecasting, and missing data imputation. These methods rely on sequential FCD time series, often complemented by loop detector measurements and calendar-based information, and are effective in capturing temporal dependencies and recurrent patterns. Their key advantage lies in enabling accurate short- and medium-term predictions, even under sparse data conditions, supporting real-time traffic management and predictive mobility applications. Statistical or traffic-modelling approaches were reported in 82 publications (49.7%), while map-matching and trajectory-processing procedures were identified in 67 publications (40.6%).

Pattern detection and spatial analysis methods aim at identifying spatiotemporal structures and behavioural regularities in large-scale datasets. Techniques such as SOM, Kernel Density Estimation (KDE), GAN, and LSTM-based models are commonly applied to congestion analysis, emission modelling, and driving behaviour recognition. By combining FCD with spatial information, taxi Global Positioning System (GPS) data, and environmental context, these approaches support the detection of traffic hotspots, anomalous patterns, and spatial heterogeneity, improving the interpretability of complex traffic phenomena.

Data fusion and pre-processing techniques form a complementary methodological category focused on improving data quality and structural consistency prior to higher-level analysis. Approaches such as the Adaptive Smoothing Method (ASM), Phase-Based Smoothing Method (PSM), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and CNN applied to image-transformed GPS data are primarily used for noise reduction, lane detection, and the integration of heterogeneous data sources. These methods typically combine FCD with BT data, loop detector measurements, and transformed trajectory representations, resulting in enhanced accuracy, robustness, and adaptability across diverse sensing configurations.

From a more specific perspective, the first group of processing categories concerns temporal modeling and forecasting, which aims to represent and predict the temporal evolution of traffic-related variables, such as speed, travel time, demand, or vehicle availability, by learning dependencies and patterns within time-series data. These approaches capture traffic dynamics over time and enable short- to medium-term predictions of future conditions through time-series analysis techniques such as LSTM networks, ARIMA models, and SVR. An LSTM-based framework applied to free-floating car-sharing data, for example, demonstrated superior performance compared to ARIMA and SVR models, particularly during peak hours, by leveraging Min–Max normalization and hourly aggregation to learn complex temporal patterns [152].

Travel time estimation represents another extensively investigated objective within FCD processing. In this context, Ref. [25] proposed a phase-based model that decomposes trips into acceleration, cruising, and deceleration components, combining a modified Bureau of Public Roads (BPR) function with shockwave theory and validating the approach using both FCD and loop detector data collected in Shanghai.

In scenarios characterized by sparse or incomplete FCD coverage, tensor-based imputation strategies have been explored. Specifically, three-dimensional tensor representations incorporating temporal, spatial, and calendar dimensions have been coupled with Tucker decomposition to reconstruct missing values, outperforming matrix-based alternatives even under low data penetration conditions [153]. Accurate travel time prediction also underpins advanced routing and navigation applications, as demonstrated by an LSTM-based system trained on spatial and temporal features in Istanbul, which significantly reduced prediction errors compared to traditional approaches and proved suitable for real-time traffic applications [154].

Beyond temporal modeling, the second group of processing categories concerns pattern detection and spatial analysis, which represent the methodological layer aimed at extracting spatial structures, behavioral regularities, and recurrent patterns from FCD. Rather than predicting future states, these approaches focus on identifying how traffic phenomena are distributed and organized in space and time, enabling the interpretation of congestion dynamics, mobility behaviors, and anomalous conditions across networks. Machine learning and deep learning techniques are commonly employed to uncover such patterns from spatio-temporal data. For instance, SOM has been used to cluster intersection traffic states based on delay indices derived from average speeds, providing interpretable visualizations of daily traffic dynamics [123]. KDE has been applied to large-scale taxi GPS datasets to detect congestion hotspots by identifying spatially and temporally persistent clusters of low-speed and stop events, as demonstrated in a study in Wuhan (China) that used more than 85 million GPS points [29]. Machine-learning techniques were reported in 52 publications (31.5%), and spatial-analysis or clustering methods in 49 publications (29.7%). Deep-learning or computer-vision approaches were identified in 28 publications (17.0%).

Vehicle trajectory prediction further extends this analytical paradigm, with deep learning models such as LSTM and GANs being employed to estimate future movements. While LSTM models perform well under stable conditions, GANs have proven more effective in generating multiple plausible trajectories in complex scenarios [28].

Beyond traffic-focused analytics, FCD-related processing pipelines have also been developed for road surface and pavement condition inference using inertial and onboard sensing. In smartphone-based approaches, preprocessing typically includes signal conditioning and geo-referencing, followed by feature extraction in the time and/or frequency domain and the estimation of roughness or quality indicators. Examples include Root Mean Square (RMS)-based acceleration metrics and transient event detection [55], frequency-domain analysis coupled with regression models to relate vibration signatures to roughness indices [86–88], and noise-reduction plus geo-referencing pipelines combined with machine-learning regression to produce road quality indexes [90]. Unsupervised or supervised learning is then used for classification tasks, relying on statistical features in time and frequency domains [89], clustering-based segment analytics [94], wavelet-based featurization with unsupervised clustering [97], and uncertainty-aware inference frameworks such as Dempster–Shafer Theory for anomaly detection [115]. Related implementations address road anomaly identification through filtering, anomaly segmentation, and threshold-based detection [106], as well as classification models that distinguish multiple defect types (e.g., potholes, speed bumps, manholes) [164] or combine neural networks with multinomial logistic regression for pavement condition classification [91].In connected-vehicle and fleet settings, processing frequently focuses on calibration and validation, including correlation with reference profilers, bias correction, and segment-level aggregation. Representative examples include linear correlation and segment analysis validated against inertial profilers [81], and regression-based comparisons with survey/auscultation data [116]. Broader in-vehicle sensing paradigms also integrate machine learning for classification of road materials and hazards [117] and physics-based validation of acceleration signals combined with multi-vehicle data fusion in cooperative contexts [165].

FCD processing has also been applied to environmental analysis, for example, using Vehicle Specific Power (VSP) to estimate electric vehicle energy consumption by road type, revealing higher consumption on urban roads and highlighting the relevance of road-aware routing strategies [68].

https://doi.org/10.3390/infrastructures11080257

The last relevant processing category concerns data fusion and preprocessing techniques, which represent the set of methodological operations aimed at transforming raw FCD into consistent, noise-reduced, and structurally aligned inputs suitable for higher-level analysis. Rather than producing final traffic or infrastructure indicators, these techniques enable the integration, synchronization, and harmonization of heterogeneous data sources, thereby providing a reliable foundation for subsequent modeling, prediction, and classification tasks. In this context, data fusion and preprocessing approaches integrate FCD with fixed sensor data, such as inductive loops and Bluetooth detectors, to improve the accuracy of speed and travel time estimates. Approaches such as the ASM and the Phase-Based Smoothing Method (PBSM), including dynamic weighting variants like Phase-Based Smoothing Method (Weighted variant) (PSM-W), have demonstrated reduced estimation errors when validated against real traffic measurements [124]. Clustering algorithms also play a central role in preprocessing, with techniques such as DBSCAN used to filter noisy GPS points before higher-level analysis. In one study, DBSCAN-based cleaning was combined with image transformation and a convolutional neural network (LeNet-5) to estimate the number of lanes on a road segment, achieving an accuracy of 92.7% and illustrating the potential of hybrid clustering–deep learning pipelines for spatial classification tasks [55]. Data-fusion procedures were reported in 41 publications (24.8%), while signal-processing approaches were identified in 31 publications (18.8%).

A further methodological branch within the data fusion and preprocessing category concerns vision-based pavement distress processing, where FCD-adjacent data streams, such as images or videos acquired from moving platforms, are transformed into detection or segmentation outputs through deep learning techniques. In this context, vision-based approaches are treated as a specific form of data preprocessing and fusion, as they aim to extract structured pavement condition indicators from raw visual inputs and, in some cases, to integrate them with other onboard sensing modalities. Representative approaches include deep neural networks applied to two-dimensional pavement images for roughness-related inference [125], CNN-based models trained and tested on labeled crack-image datasets [126,127], and architectures that combine multiscale feature fusion and deep supervision to improve segmentation accuracy [166]. Recent work increasingly incorporates transformer components, including Vision Transformer comparisons against common CNN backbones [128] and hybrid CNN–transformer segmentation networks with dedicated fusion modules and lightweight decoders [129]. Several studies also emphasize the role of datasets and benchmarking pipelines, proposing large-scale labeled crack datasets and evaluating segmentation baselines enhanced with attention mechanisms or self-supervised learning strategies [167].

Hybrid pipelines that combine vision with inertial sensing typically require synchronization and cross-modal alignment, such as video frame analysis coupled with accelerometer z-axis profile reconstruction and GPS-based synchronization [107], or joint anomaly detection of accelerometer signals with semantic segmentation of imagery [109]. Finally, integrated monitoring systems combine heterogeneous sensors, data fusion, and GIS-oriented visualization to support decision-making workflows, including statistical condition estimation and map-based reporting [168].

A further critical aspect emerging from the reviewed studies concerns the limited standardization of data processing and validation procedures across different FCD applications. Although advanced machine learning, signal processing, and data fusion techniques frequently achieve promising results under controlled experimental conditions, their reproducibility and transferability across heterogeneous datasets and operational contexts are often insufficiently assessed. In particular, relatively few studies explicitly evaluate the sensitivity of processing pipelines to variations in vehicle characteristics, sensor quality, sampling frequency, or environmental conditions. Consequently, despite the growing methodological sophistication of FCD analytics, the transition from experimental implementations to robust operational deployment remains only partially achieved, especially for infrastructure-monitoring applications.

To summarise, the analysis shows that data processing methodologies for FCD are well established for traffic-oriented objectives, with a wide adoption of advanced temporal modeling, spatial analysis, and machine learning techniques. Nevertheless, these approaches are often developed and validated within narrowly defined problem settings, and their generalization across heterogeneous data sources, sensing configurations, and operational contexts remains limited. Relatively few studies address the joint challenges of multi-sensor integration, fleet-level aggregation, and long-term robustness within unified processing pipelines, indicating an open research gap toward scalable and transferable data processing frameworks.

3.3. Key Findings Emerging from the Results

Taken together, the results confirm the predominance of traffic- and mobility-oriented applications, which accounted for 100 of the 165 eligible publications (60.6%), compared with 20 publications (12.1%) primarily addressing infrastructure monitoring. Although accelerometers, gyroscopes, or IMUs were identified in 29 publications (17.6%), only 9 studies (5.5%) reported an explicit PMS-oriented integration. Moreover, only 15 publications (9.1%) described an operational or real-time deployment, indicating a substantial gap between experimental sensing capabilities and their systematic implementation in pavement-management processes.

4. Discussion

The results of this systematic review show that FCD have reached a high level of maturity in the analysis and management of transport systems, particularly in applications related to traffic dynamics, mobility patterns, congestion monitoring, routing optimization, and environmental assessment. Over the past two decades, advances in onboard sensing technologies, vehicle connectivity, and data-driven analytics have consolidated FCD as a reliable and scalable source of information for mobility-oriented studies. However, the reviewed literature also reveals a clear asymmetry in the exploitation of FCD, with infrastructure-related applications remaining comparatively underdeveloped. This observation is consistent with prior review contributions that frame FCD from a technology-system perspective [1]. Traffic-state estimation and mobility-planning studies jointly represented 60.6% of the corpus, whereas infrastructure monitoring accounted for 12.1%.

A recurring pattern in the analyzed studies is that research on road surface conditions or physical infrastructure often relies on ad hoc data collection strategies. These typically involve specially instrumented vehicles, dedicated sensing platforms, or experimental measurement campaigns explicitly designed for pavement or road anomaly detection. While such approaches enable controlled, high-quality observations, they are inherently limited in scalability, automation, and continuous network-wide coverage. In contrast, the large volumes of data passively generated by ordinary circulating vehicle fleets are predominantly exploited for traffic-centric analyses, despite the widespread availability of onboard sensors capable of capturing signals sensitive to road surface irregularities.

This underutilization is particularly evident in accelerometric signals. Although modern vehicles routinely record acceleration data through embedded sensors and telematics systems, accelerometric or inertial sensing was reported in 29 publications (17.6% of the corpus), but explicit PMS-oriented integration was identified in only 9 publications (5.5%). When accelerometers are considered, their use is generally confined to vehicle dynamics analysis, odometry, or driving behavior classification, rather than to the characterization of pavement-related phenomena. As a result, the accelerometric dimension of FCD remains fragmented and marginal within the broader FCD research landscape.

The review further indicates that this limitation is primarily methodological rather than technological. In this context, "methodological" does not refer to the lack of signal processing or machine learning techniques, which are widely available, but to the absence of consolidated frameworks for aggregating, normalizing, and interpreting accelerometric data at the fleet level. Existing FCD research has largely prioritized precision at the individual vehicle or trajectory level, whereas infrastructure-related phenomena inherently require a statistical, fleet-level perspective. Aggregating accelerometric signals across heterogeneous vehicles, time periods, and driving conditions would mitigate localized noise, vehicle-specific effects, and isolated outliers, enabling the identification of road segments with a higher probability of surface anomalies or progressive degradation. However, consolidated frameworks supporting such statistical exploitation of fleet-wide FCD are currently lacking.

From an operational perspective, the reviewed approaches reveal a series of trade-offs that currently limit the large-scale deployment of FCD-based infrastructure monitoring systems. Smartphone-based sensing solutions provide clear advantages in terms of low implementation cost, scalability, and crowdsourcing potential, but their reliability is often influenced by vehicle characteristics, sensor positioning, driving behaviour, speed variability, and heterogeneous acquisition conditions. Conversely, dedicated onboard sensors and connected-vehicle platforms generally provide higher-quality and more stable signals, although they require more complex calibration procedures, controlled sensing configurations, and, in some cases, access to proprietary vehicle data. Similarly, vision-based approaches offer increasingly accurate pavement distress detection capabilities, particularly when combined with deep learning techniques, but remain sensitive to environmental conditions, illumination variability, and computational requirements. These observations suggest that no single sensing or processing strategy currently satisfies all operational requirements simultaneously. Rather, future FCD-based pavement monitoring frameworks will likely depend on the integration of complementary sensing technologies and robust multi-source data fusion pipelines capable of balancing scalability, accuracy, robustness, and operational feasibility.

The comparative analysis conducted throughout the review highlights several recurring methodological and operational gaps that currently limit the large-scale deployment of FCD-based infrastructure monitoring systems. These gaps do not primarily concern sensing availability, but rather the lack of standardized operational frameworks, robust validation procedures, and transferable fleet-level methodologies. Table 13 summarizes the principal research gaps identified across the reviewed literature and their implications for future FCD-based pavement monitoring applications.

At the same time, the literature demonstrates the availability of advanced analytical tools (such as multi-source data fusion, machine learning techniques, and spatiotemporal modeling) that are routinely applied to mobility analysis. The limited extension of these methods to infrastructure-oriented applications suggests a misalignment between analytical capabilities and application domains within current FCD research. Addressing this misalignment represents a key opportunity to broaden the scope of FCD beyond traffic performance assessment toward more comprehensive monitoring of road network conditions, while remaining fully within the FCD paradigm.

In this context, the development of standardized operational frameworks and validation procedures emerges as one of the main priorities for future research.

Table 13. Main research gaps emerging from the reviewed literature and their implications for the operational deployment of FCD-based infrastructure monitoring systems.

Research Gap	Main Implication
Lack of fleet-level standardization	Limited scalability and interoperability
Strong dependence on vehicle characteristics	Reduced transferability across heterogeneous fleets
Limited calibration standardization	Reduced comparability among studies
Small-scale experimental datasets	Weak generalization capability
Inconsistent validation procedures	Limited comparability and uncertain reliability across studies
Scarce long-term monitoring studies	Uncertain reliability under real operational conditions
Heterogeneous sensing configurations	Reproducibility challenges
Limited integration into PMS frameworks	Reduced practical applicability

The table highlights the principal methodological and operational gaps emerging from the reviewed studies, emphasizing the current limitations affecting the large-scale deployment, standardization, and transferability of FCD-based pavement monitoring systems.

The geographical distribution of the included studies was uneven. Countries with a moderate number of publications provide useful evidence for comparative interpretation, but they do not necessarily support robust country-specific inference. This imbalance may reflect differences in data availability, fleet penetration, institutional access, privacy and governance frameworks, and investment in intelligent transport systems, and it limits the direct transferability of some findings across national and transport-system contexts.

Despite the systematic structure adopted in this review, some limitations should be acknowledged. The reviewed literature is characterized by substantial heterogeneity in sensing configurations, validation procedures, experimental scales, and operational contexts, limiting the possibility of direct quantitative comparison among studies. Furthermore, the extended interpretation of FCD adopted in this work includes heterogeneous vehicle-borne sensing paradigms that may partially overlap with adjacent mobile sensing approaches. Nevertheless, this broader perspective was intentionally adopted to capture the evolving integration between mobile sensing technologies and infrastructure monitoring applications.

A further methodological limitation concerns the use of a single reviewer for study selection, data extraction, and methodological appraisal. Although predefined criteria and a documented decision process were adopted to reduce subjectivity, reviewer-dependent selection, extraction, or classification bias cannot be completely excluded.

Operational Pathway for Integrating Accelerometric FCD into PMS

To translate accelerometric FCD from experimental sensing into an operational Pavement Management System, the evidence reviewed in this study suggests a six-stage pathway linking data acquisition to maintenance decision-making (Table 14).

First, accelerometric measurements should be acquired together with synchronized positioning, timestamp, speed, and essential vehicle and sensor metadata. This information is required to distinguish road-induced responses from variations associated with vehicle characteristics, sensor placement, and operating conditions.

Second, the raw signals should undergo quality control and preprocessing, including sensor-axis alignment, gravity compensation where required, filtering, removal of implausible observations, temporal synchronization, map matching, and segmentation according to homogeneous road sections.

Third, measurements should be normalized to reduce the influence of speed, vehicle type, suspension characteristics, tyre conditions, sensor configuration, and device heterogeneity. Calibration over reference road sections or the use of statistical correction models may support comparability among different vehicles and acquisition campaigns.

Table 14. Proposed operational pathway for integrating accelerometric FCD into Pavement Management Systems.

Stage	Principal Operations	Main Output	PMS Function
Data acquisition	Accelerometer/IMU, GNSS, timestamp, speed, and vehicle and sensor metadata.	Synchronized georeferenced observations.	Traceable raw monitoring data.
Quality control and preprocessing	Filtering, orientation correction, synchronization, outlier removal, map matching, and road segmentation.	Cleaned signals associated with road segments.	Reliable analytical input.
Normalization and calibration	Correction for speed, vehicle type, suspension, tyres, sensor location, and device characteristics.	Comparable normalized indicators.	Cross-vehicle consistency.
Fleet-level aggregation	Combination of repeated passages using robust statistics, persistence analysis, and confidence scoring.	Segment-level condition or anomaly indicators.	Network-wide screening.
Validation and data fusion	Comparison with profiler measurements, IRI, inspections, or distress inventories; fusion with imagery and contextual data.	Validated condition estimates with uncertainty information.	Reliable condition assessment.
PMS integration and feedback	Condition classes, thresholds, inspection triggers, maintenance prioritization, and post-intervention updating.	Decision-ready PMS information layer.	Planning, prioritization, and continuous updating.

The framework synthesizes the methodological requirements and recurring limitations identified in the reviewed literature. It should be interpreted as a proposed operational pathway rather than as a validated universal implementation standard.

Fourth, normalized observations should be aggregated at fleet and road-segment level. Multiple passages should be combined using robust statistical indicators, persistence criteria, and confidence measures so that isolated events and vehicle-specific noise do not directly generate pavement-condition alerts.

Fifth, the resulting indicators should be validated against independent reference measurements, such as inertial-profiler surveys, International Roughness Index values, visual inspections, or verified pavement-distress inventories. Their reliability may be further improved through fusion with vehicle-mounted imagery, maintenance records, traffic exposure, weather information, and other contextual data.

Finally, validated segment-level indicators should be translated into PMS-compatible outputs, including condition classes, anomaly probability, severity or reliability scores, inspection triggers, and maintenance-priority rankings. Subsequent inspections and maintenance interventions should provide feedback for periodic recalibration and continuous improvement of the monitoring framework.

This pathway does not imply that a single universal model can be applied to every fleet or road network. Rather, it defines the minimum functional stages required to support transparent, transferable, and progressively scalable integration of accelerometric FCD into pavement-management decision processes.

5. Conclusions

This systematic review examined the development of Floating Car Data (FCD) research across transportation applications and showed that the field has reached substantial methodological maturity in traffic- and mobility-oriented domains. The evidence base is strongly concentrated around applications in which trajectory-derived variables can be directly transformed into operational indicators, such as speed, travel time, congestion patterns, route choice, and mobility dynamics. This explains why travel and traffic-state estimation and mobility-planning applications represent the dominant part of the reviewed literature, accounting together for 100 of the 165 eligible publications (60.6%).

By contrast, the use of FCD for road-infrastructure monitoring remains considerably less developed. Infrastructure monitoring was identified as the primary application domain in only 20 publications (12.1%), and explicit integration with Pavement Management Systems (PMS) was reported in only 9 studies (5.5%). This imbalance indicates that the main limitation is not the absence of vehicle-generated data or onboard sensing technologies. GPS/GNSS trajectories, onboard telemetry, accelerometers, inertial sensors, smartphones, black boxes, and vehicle-mounted devices are already present in the literature. The critical gap lies instead in the transition from data availability and experimental feasibility to standardized, validated, and operationally transferable infrastructure-monitoring frameworks.

The results therefore suggest that FCD research is currently shaped by an asymmetry between sensing potential and operational use. Traffic-oriented applications benefit from relatively mature indicators, established processing pipelines, large-scale datasets, and clearer validation targets. Pavement-condition applications, instead, require the interpretation of vehicle–road interaction signals that are affected by vehicle type, speed, suspension characteristics, tyre conditions, sensor placement, sampling frequency, environmental conditions, and driving behaviour. These factors cannot be treated as secondary sources of noise; they are central methodological variables that must be normalized, calibrated, or statistically controlled before accelerometric FCD can support reliable infrastructure-management decisions.

A further pattern emerging from the review concerns the scale of implementation. Many infrastructure-oriented studies demonstrate the feasibility of extracting road-surface information from vehicle-borne sensing, but they often remain limited to specific vehicles, controlled experiments, individual routes, short observation periods, or small fleets. Only 15 publications (9.1%) reported operational or real-time deployment. This indicates a transition gap between methodological proof of concept and network-wide implementation. The key research challenge is therefore not simply to improve individual detection algorithms, but to move from vehicle-level measurements to fleet-level statistical aggregation, where repeated observations from heterogeneous vehicles can be transformed into robust segment-level indicators, confidence scores, inspection triggers, and maintenance-priority information.

The geographical distribution of the evidence also provides an important interpretation of the field. The uneven distribution of studies across countries should not be understood only as a bibliographic feature, but also as an indication of the conditions that enable FCD research and deployment. Differences in data access, fleet penetration, institutional capacity, collaboration between researchers and road authorities, privacy and governance arrangements, and investment in intelligent transport systems influence where FCD applications can be developed and validated. As a result, the findings of the review should be interpreted as a systematic synthesis of the available international evidence, rather than as proof of uniform global maturity or transferability.

The main contribution of this review is therefore twofold. First, it provides a structured evidence map showing that FCD research is mature for traffic and mobility applications but remains fragmented for infrastructure monitoring and PMS-oriented use. Second, it identifies the operational pathway required to address this gap: accelerometric FCD should be acquired together with positioning, speed, vehicle, and sensor metadata; preprocessed and map-matched to road segments; normalized across vehicles and operating conditions; aggregated at fleet and segment level; validated against independent pavement-condition measurements; fused with complementary data sources; and translated into PMS-compatible indicators.

In addition, the integration of FCD-derived pavement indicators with road-safety and crash-risk models represents a promising research direction. The increasing availability of continuous vehicle-generated data has already proved valuable for monitoring transport system performance, diagnosing operational conditions, and supporting data-driven decision making in public transport systems [169–172]. Extending these approaches to pavement monitoring could enable the integration of infrastructure conditions with road-safety and crash-risk models. Since pavement condition may act as a contributing factor in road-safety risk, future studies could investigate how continuous vehicle-derived monitoring, historical crash data, and near-miss indicators can be jointly used to support proactive infrastructure management and safety-oriented maintenance prioritization [173–175].

Future research should consequently focus less on demonstrating that vehicle-borne sensors can detect individual road anomalies and more on developing transferable frameworks for continuous, network-wide pavement assessment. Priority should be given to fleet-level normalization, cross-site validation, long-term monitoring, uncertainty quantification, multi-source data fusion, and the integration of FCD-derived indicators into existing maintenance-planning processes. In this perspective, the future development of FCD for infrastructure management depends not only on technological progress, but also on methodological standardization, institutional data-governance arrangements, and the ability of road authorities to incorporate new dynamic indicators into operational PMS workflows.

Author Contributions: Conceptualization, S.S. and B.B.; methodology, B.B. and S.S.; investigation, S.S.; data curation, S.S.; formal analysis, S.S.; writing—original draft preparation, S.S.; writing—review and editing, S.S., R.V. and B.B.; supervision, B.B. and R.V. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding. The work was carried out within the PhD Programme (38th cycle) at the University of Brescia (DICACIM).

Data Availability Statement: The bibliographic metadata analysed in this review were obtained from Scopus and Google Scholar. The derived record-level screening, eligibility, coding, and methodological-appraisal data are available from the corresponding author upon reasonable request. Original database exports may be subject to the licensing conditions of the respective providers.

Acknowledgments: During the preparation of this manuscript, the author(s) used ChatGPT-5.6 (OpenAI) to support language refinement and improve textual clarity. The author(s) have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

ARIMA	AutoRegressive Integrated Moving Average
ASM	Adaptive Smoothing Method
BT	Bluetooth
BPR	Bureau of Public Roads (function)
CAN	Controller Area Network
CNN	Convolutional Neural Network
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
ETC	Electronic Toll Collection
FCD	Floating Car Data
GAN	Generative Adversarial Network

GLONASS	Global Navigation Satellite System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IMU	Inertial Measurement Unit
IoT	Internet of Things
IRI	International Roughness Index
ITS	Intelligent Transportation Systems
KDE	Kernel Density Estimation
LSTM	Long Short-Term Memory
ML	Machine Learning
OBD	On-Board Diagnostics
OEM	Original Equipment Manufacturer
POI	Point of Interest
PSM	Phase-Based Smoothing Method
PSM-W	Phase-Based Smoothing Method (Weighted variant)
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RMS	Root Mean Square
SOM	Self-Organizing Map
SULP	Sustainable Urban Logistics Plan
SVR	Support Vector Regression
UAV	Unmanned Aerial Vehicle
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VSP	Vehicle Specific Power
YOLO	You Only Look Once

References

1. Budimir, D.; Jelušić, N.; Perić, M. Floating Car Data Technology. *Sci. J. Marit. Res.* **2019**, *33*, 22–32. [CrossRef]
2. Mazzi, C.; Carini, C.; Meocci, M.; Paliotto, A.; Marradi, A. Floating Car Data for Road Roughness: An Innovative Approach to Optimize Road Surface Monitoring and Maintenance. *Future Transp.* **2025**, *5*, 162. [CrossRef]
3. Zhang, C.; Zhou, Y.; Zhang, M.; Wang, B.; Nie, Y. Review and prospect of floating car data research in transportation. *J. Traffic Transp. Eng. (Engl. Ed.)* **2025**, *12*, 752–771. [CrossRef]
4. Liberati, A.; Altman, D.G.; Tetzlaff, J.; Mulrow, C.; Gøtzsche, P.C.; Ioannidis, J.P.A.; Clarke, M.; Devereaux, P.J.; Kleijnen, J.; Moher, D. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. *J. Clin. Epidemiol.* **2009**, *62*, e1–e34. [CrossRef] [PubMed]
5. Barabino, B.; Lai, C.; Olivo, A. Fare evasion in public transport systems: A review of the literature. *Public Transp.* **2020**, *12*, 27–88. [CrossRef]
6. Boglietti, S.; Barabino, B.; Maternini, G. Survey on e-powered micro personal mobility vehicles: Exploring current issues towards future developments. *Sustainability* **2021**, *13*, 3692. [CrossRef]
7. Barabino, B.; Carra, M.; Currie, G. Fare inspection in proof-of-payment transit networks: A review. *J. Public Transp.* **2024**, *26*, 100101. [CrossRef]
8. Yuan, Y.; Van Lint, H.; Van Wageningen-Kessels, F.; Hoogendoorn, S. Network-wide traffic state estimation using loop detector and floating car data. *J. Intell. Transp. Syst. Technol. Plan. Oper.* **2014**, *18*, 41–50. [CrossRef]
9. Erdelić, T.; Carić, T.; Erdelić, M.; Tišljarić, L.; Turković, A.; Jelušić, N. Estimating congestion zones and travel time indexes based on the floating car data. *Comput. Environ. Urban Syst.* **2021**, *87*, 101604. [CrossRef]
10. Li, J.; Boonaert, J.; Doniec, A.; Lozenguez, G. Multi-models machine learning methods for traffic flow estimation from Floating Car Data. *Transp. Res. Part C Emerg. Technol.* **2021**, *132*, 103389. [CrossRef]
11. Vandenberghe, W.; Vanhauwaert, E.; Verbrugge, S.; Moerman, I.; Demeester, P. Feasibility of expanding traffic monitoring systems with floating car data technology. *IET Intell. Transp. Syst.* **2012**, *6*, 347–354. [CrossRef]
12. Sunderrajan, A.; Viswanathan, V.; Cai, W.; Knoll, A. Traffic state estimation using floating car data. *Procedia Comput. Sci.* **2016**, *80*, 2008–2018. [CrossRef]
13. Liu, X.; Lu, F.; Zhang, H.; Qiu, P. Intersection delay estimation from floating car data via principal curves: A case study on Beijing's road network. *Front. Earth Sci.* **2013**, *7*, 206–216. [CrossRef]

14. Astarita, V.; Giofrè, V.P.; Guido, G.; Vitale, A. A single intersection cooperative-competitive paradigm in real time traffic signal settings based on floating car data. *Energies* **2019**, *12*, 409. [CrossRef]
15. Protschky, V.; Ruhhammer, C.; Feit, S. Learning Traffic Light Parameters with Floating Car Data. In *Proceedings of the IEEE Conference on Intelligent Transportation Systems*; IEEE: New York, NY, USA, 2015; pp. 2438–2443. [CrossRef]
16. Wang, X.; Liu, H.; Yu, R.; Deng, B.; Chen, X.; Wu, B. Exploring operating speeds on urban arterials using floating car data: Case study in Shanghai. *J. Transp. Eng.* **2014**, *140*, 04014044. [CrossRef]
17. Dakic, I.; Menendez, M. On the use of Lagrangian observations from public transport and probe vehicles to estimate car space-mean speeds in bi-modal urban networks. *Transp. Res. Part C Emerg. Technol.* **2018**, *91*, 317–334. [CrossRef]
18. Wang, X.; Peng, L.; Chi, T.; Li, M.; Yao, X.; Shao, J. A hidden markov model for urban-scale traffic estimation using floating car data. *PLoS ONE* **2015**, *10*, e0145348. [CrossRef] [PubMed]
19. Li, Z.-H.; Zheng, S.-T.; Jiang, R.; Tian, J.F.; Zhu, K.X.; Di Pace, R. Empirical and simulation study on traffic oscillation characteristic using floating car data. *Phys. A Stat. Mech. Appl.* **2022**, *605*, 127973. [CrossRef]
20. Ipekyuz, B.; Sevinen, P.K.; Yaman, H.T. Performance Evaluation of Fused Floating Car Data (FCD) and Bluetooth (BT) Data Speed Estimation on Urban Arterials. *Arab. J. Sci. Eng.* **2025**, *50*, 17091–17108. [CrossRef]
21. Teng, W.; Liu, F.; Yang, J.; Shi, C.; Zhang, Y.; Wang, F. Uncovering the Uncertainties and Variability of Travel Time and Fuel Consumption Using Floating Car Data: A Case Study in Wuhan. *IEEE Access* **2025**, *13*, 139098–139109. [CrossRef]
22. Chen, B.Y.; Yuan, H.; Li, Q.; Lam, W.H.; Shaw, S.L.; Yan, K. Map-matching algorithm for large-scale low-frequency floating car data. *Int. J. Geogr. Inf. Sci.* **2014**, *28*, 22–38.
23. Rahmani, M.; Jenelius, E.; Koutsopoulos, H.N. Non-parametric estimation of route travel time distributions from low-frequency floating car data. *Transp. Res. Part C Emerg. Technol.* **2015**, *58*, 343–362. [CrossRef]
24. Rahmani, M.; Koutsopoulos, H.N. Path inference from sparse floating car data for urban networks. *Transp. Res. Part C Emerg. Technol.* **2013**, *30*, 41–54. [CrossRef]
25. Zheng, L.; Ma, H.; Wang, Z. Travel Time Estimation for Urban Arterials Based on the Multi-Source Data. *Sustainability* **2024**, *16*, 7845. [CrossRef]
26. Schweppenhäuser, M.; Schrab, K.; Protzmann, R.; Radusch, I. Evaluating spatiotemporal speed metrics for traffic state estimation on complex urban roads. *Simulation* **2025**, *102*, 7–18. [CrossRef]
27. Zhang, Y.; Zuo, X.; Zhang, L.; Chen, Z. Traffic congestion detection based on GPS floating-car data. *Procedia Eng.* **2011**, *15*, 5541–5546. [CrossRef]
28. Rossi, L.; Ajmar, A.; Paolanti, M.; Pierdicca, R. Vehicle trajectory prediction and generation using LSTM models and GANs. *PLoS ONE* **2021**, *16*, e0253868. [CrossRef] [PubMed]
29. Liu, X.; Ban, Y. Uncovering Spatio-temporal cluster patterns using massive floating car data. *ISPRS Int. J. Geo-Inf.* **2013**, *2*, 371–384. [CrossRef]
30. Dewulf, B.; Neutens, T.; Vanlommel, M.; Logghe, S.; De Maeyer, P.; Witlox, F.; De Weerdt, Y.; Van de Weghe, N. Examining commuting patterns using Floating Car Data and circular statistics: Exploring the use of new methods and visualizations to study travel times. *J. Transp. Geogr.* **2015**, *48*, 41–51. [CrossRef]
31. Croce, A.I.; Musolino, G.; Rindone, C.; Vitetta, A. Estimation of travel demand models with limited information: Floating car data for parameters' calibration. *Sustainability* **2021**, *13*, 8838. [CrossRef]
32. Jiao, W.; Huang, W.; Fan, H. Evaluating spatial accessibility to healthcare services from the lens of emergency hospital visits based on floating car data. *Int. J. Digit. Earth* **2022**, *15*, 108–133. [CrossRef]
33. Ertugay, K.; Duzgun, S. GIS-based stochastic modeling of physical accessibility using GPS-based floating car data and Monte Carlo simulation. *Int. J. Geogr. Inf. Sci.* **2011**, *25*, 1491–1506. [CrossRef]
34. Nuzzolo, A.; Comi, A.; Papa, E.; Polimeni, A. Understanding taxi travel demand patterns through floating car data. *Adv. Intell. Syst. Comput.* **2019**, *879*, 445–452. [CrossRef]
35. Bauer, D.; Richter, G.; Asamer, J.; Heilmann, B.; Lenz, G.; Kölbl, R. Quasi-Dynamic Estimation of OD Flows from Traffic Counts Without Prior OD Matrix. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 2025–2034. [CrossRef]
36. Jahnke, M.; Ding, L.; Karja, K.; Wang, S. Identifying origin/destination hotspots in floating car data for visual analysis of traveling behavior. In *Progress in Location-Based Services 2016; Lecture Notes in Geoinformation and Cartography*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 253–269. [CrossRef]
37. Mitra, A.; Attanasi, A.; Meschini, L.; Gentile, G. Methodology for O-D matrix estimation using the revealed paths of floating car data on large-scale networks. *IET Intell. Transp. Syst.* **2020**, *14*, 1704–1711. [CrossRef]
38. Comi, A.; Polimeni, A. Estimating Path Choice Models through Floating Car Data. *Forecasting* **2022**, *4*, 525–537. [CrossRef]
39. Comi, A.; Rossolov, A.; Polimeni, A.; Nuzzolo, A. Private car O-D flow estimation based on automated vehicle monitoring data: Theoretical issues and empirical evidence. *Information* **2021**, *12*, 493. [CrossRef]
40. Sun, D.; Leurent, F.; Xie, X. Discovering vehicle usage patterns on the basis of daily mobility profiles derived from floating car data. *Transp. Lett.* **2021**, *13*, 163–171. [CrossRef]

41. Sun, D.J.; Zhang, C.; Zhang, L.; Chen, F.; Peng, Z.-R. Urban travel behavior analyses and route prediction based on floating car data. *Transp. Lett.* **2014**, *6*, 118–125. [CrossRef]
42. De Vincentis, M.; Filippi, F.; Gori, S. A Data-Driven Approach to Analyze Mobility Patterns and the Built Environment: Evidence from Brescia, Catania, and Salerno (Italy). *Sustainability* **2022**, *14*, 14378. [CrossRef]
43. Gao, Y.; Liao, Y. Urban Tourism Traffic Analysis Zone Division Based on Floating Car Data. *Promet Traffic Transp.* **2023**, *35*, 395–406. [CrossRef]
44. Garcia-Castro, A.; Monzon, A. Homogenization effects of variable speed limits. *Transp. Telecommun.* **2014**, *15*, 130–143. [CrossRef]
45. Garcia-Castro, A.; Monzon, A. Using floating car data to analyse the effects of ITS measures and Eco-driving. *Sensors* **2014**, *14*, 21358–21374. [CrossRef] [PubMed]
46. Li, Q.; Zhang, T.; Wang, H.; Zeng, Z. Dynamic accessibility mapping using floating car data: A network-constrained density estimation approach. *J. Transp. Geogr.* **2011**, *19*, 379–393. [CrossRef]
47. Sun, S.; Duan, Z.; Yang, D. Urban freight management with stochastic time-dependent travel times and application to large-scale transportation networks. *Discret. Dyn. Nat. Soc.* **2015**, *2015*, 914309. [CrossRef]
48. Comi, A.; Persia, L.; Polimeni, A.; Campagna, A. A methodology to design and assess scenarios within SULPs: The case of Bologna. *Transp. Res. Procedia* **2020**, *46*, 269–276. [CrossRef]
49. Croce, A.I.; Musolino, G.; Rindone, C.; Vitetta, A. Route and path choices of freight vehicles: A case study with floating car data. *Sustainability* **2020**, *12*, 8557. [CrossRef]
50. Battaglia, G.; Musolino, G.; Vitetta, A. Freight Demand Distribution in a Suburban Area: Calibration of an Acquisition Model with Floating Car Data. *J. Adv. Transp.* **2022**, *2022*, 1535090. [CrossRef]
51. Comi, A.; Nuzzolo, A.; Polimeni, A. Aggregate delivery tour modeling through AVM data: Experimental evidence for light goods vehicles. *Transp. Lett.* **2021**, *13*, 201–208. [CrossRef]
52. Nuzzolo, A.; Comi, A.; Polimeni, A. Urban Freight Vehicle Flows: An Analysis of Freight Delivery Patterns through Floating Car Data. *Transp. Res. Procedia* **2020**, *47*, 409–416. [CrossRef]
53. Comi, A.; Polimeni, A. Forecasting Delivery Pattern through Floating Car Data: Empirical Evidence. *Future Transp.* **2021**, *1*, 707–719. [CrossRef]
54. Colombaroni, C.; Fusco, G.; Isaenko, N. Coherence analysis of road safe speed and driving behavior from floating car data. *IET Intell. Transp. Syst.* **2020**, *14*, 985–992. [CrossRef]
55. Li, X.; Zhang, Y.; Xiang, L.; Wu, T. Urban Road Lane Number Mining from Low-Frequency Floating Car Data Based on Deep Learning. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 467. [CrossRef]
56. Huang, Y.; Sun, D.; Zhang, L.-H. Effects of congestion on drivers' speed choice: Assessing the mediating role of state aggressiveness based on taxi floating car data. *Accid. Anal. Prev.* **2018**, *117*, 318–327. [CrossRef] [PubMed]
57. Wang, J.; Luo, T.; Fu, T. Crash prediction based on traffic platoon characteristics using floating car trajectory data and the machine learning approach. *Accid. Anal. Prev.* **2019**, *133*, 105320. [CrossRef] [PubMed]
58. Mahajan, V.; Katrakazas, C.; Antoniou, C. Crash Risk Estimation Due to Lane Changing: A Data-Driven Approach Using Naturalistic Data. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 3756–3765. [CrossRef]
59. Vos, J.; Farah, H.; Hagenzieker, M. Speed behaviour upon approaching freeway curves. *Accid. Anal. Prev.* **2021**, *159*, 106276. [CrossRef] [PubMed]
60. Kieć, M.; Ambros, J.; Bąk, R.; Gogolín, O. Evaluation of safety effect of turbo-roundabout lane dividers using floating car data and video observation. *Accid. Anal. Prev.* **2019**, *125*, 302–310. [CrossRef] [PubMed]
61. Xu, C.; Wang, X.; Yang, H.; Xie, K.; Chen, X. Exploring the impacts of speed variances on safety performance of urban elevated expressways using GPS data. *Accid. Anal. Prev.* **2019**, *123*, 29–38. [CrossRef] [PubMed]
62. Houbraken, M.; Logghe, S.; Schreuder, M.; Audenaert, P.; Colle, D.; Pickavet, M. Automated Incident Detection Using Real-Time Floating Car Data. *J. Adv. Transp.* **2017**, *2017*, 8241545. [CrossRef]
63. Arman, M.A.; Tampère, C.M.J. Empirical Study of Lane-Changing Maneuvers in a Weaving Area Based on Reconstructed Trajectories of Floating Car Data. *Transp. Res. Rec.* **2024**, *2678*, 219–234. [CrossRef]
64. Diependaele, K.; Riguelle, F.; Temmerman, P. Speed Behavior Indicators Based on Floating Car Data: Results of a Pilot Study in Belgium. *Transp. Res. Procedia* **2016**, *14*, 2074–2082. [CrossRef]
65. Colombaroni, C.; Fusco, G.; Isaenko, N. Analysis of Road Safety Speed from Floating Car Data. *Transp. Res. Procedia* **2020**, *45*, 898–905. [CrossRef]
66. Ambros, J.; Altmann, J.; Jurewicz, C.; Chevalier, A. Proactive assessment of road curve safety using floating car data: An exploratory study. *Arch. Transp.* **2019**, *50*, 7–15. [CrossRef]
67. Zhang, D.-Z.; Sun, D.; Peng, Z.-R. A comprehensive taxi assessment index using floating car data. *J. Harbin Inst. Technol. (New Ser.)* **2014**, *21*, 7–16.
68. Yao, E.; Yang, Z.; Song, Y.; Zuo, T. Comparison of electric vehicle's energy consumption factors for different road types. In *Discrete Dynamics in Nature and Society*; Wiley: Hoboken, NJ, USA, 2013. [CrossRef]

69. Comi, A.; Polimeni, A. Assessing potential sustainability benefits of micromobility: A new data driven approach. *Eur. Transp. Res. Rev.* **2024**, *16*, 19. [CrossRef]
70. Nigro, M.; Castiglione, M.; Maria Colasanti, F.; De Vincentis, R.; Valenti, G.; Liberto, C.; Comi, A. Exploiting floating car data to derive the shifting potential to electric micromobility. *Transp. Res. Part A Policy Pract.* **2022**, *157*, 78–93. [CrossRef]
71. Nigro, M.; Ferrara, M.; De Vincentis, R.; Liberto, C.; Valenti, G. Data driven approaches for sustainable development of e-mobility in urban areas. *Energies* **2021**, *14*, 3949. [CrossRef]
72. Chen, F.; Yin, Z.; Ye, Y.; Sun, D. Taxi hailing choice behavior and economic benefit analysis of emission reduction based on multi-mode travel big data. *Transp. Policy* **2020**, *97*, 73–84. [CrossRef]
73. Liberto, C.; Valenti, G.; Orchi, S.; Lelli, M.; Nigro, M.; Ferrara, M. The impact of electric mobility scenarios in large urban areas: The Rome case study. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 3540–3549. [CrossRef]
74. Croce, A.I.; Musolino, G.; Rindone, C.; Vitetta, A. Traffic and energy consumption modelling of electric vehicles: Parameter updating from floating and probe vehicle data. *Energies* **2022**, *15*, 82. [CrossRef]
75. Croce, A.I.; Musolino, G.; Rindone, C.; Vitetta, A. Energy consumption of electric vehicles: Models' estimation using big data (FCD). *Transp. Res. Procedia* **2020**, *47*, 211–218. [CrossRef]
76. Siverio, S.; Szozda, B.; Ponzoni, M.; Barabino, B.; Maternini, G. Integrating Floating Car Data in a Pavement Management System: Some Empirical Evidence from Brescia (Italy). *Transp. Res. Procedia* **2025**, *90*, 480–487. [CrossRef]
77. Sofia, S.; Johan, C. Comparison of methods for winter road friction estimation using systems implemented for floating car data. *Int. J. Veh. Syst. Model. Test.* **2023**, *17*, 101–111. [CrossRef]
78. Bruwer, M.M.; Andersen, S.J. Using commercial floating car data to remotely infer the presence of potholes along rural road segments. *Afr. Transp. Stud.* **2025**, *3*, 100017. [CrossRef]
79. Gyozo, G.; Can, Y. Scalable detection of traffic congestion from massive Floating Car Data streams. In *Proceedings of the 1st International ACM SIGSPATIAL Workshop on Smart Cities and Urban Analytics 2015, UrbanGIS*; Association for Computing Machinery (ACM): New York, NY, USA, 2015; pp. 111–118. [CrossRef]
80. Sollén, S.; Casselgren, J. Large-scale implementation of floating car data monitoring road friction. *IET Intell. Transp. Syst.* **2021**, *15*, 727–739. [CrossRef]
81. Mahlberg, J.; Li, H.; Zachrisson, B.; Leslie, D.K.; Bullock, D.M. Pavement Quality Evaluation Using Connected Vehicle Data. *Sensors* **2022**, *22*, 9109. [CrossRef] [PubMed]
82. Irschik, D.; Stork, W. Road surface classification for extended floating car data. In *Proceedings of the 2014 IEEE International Conference on Vehicular Electronics and Safety, ICVES*; IEEE: New York, NY, USA, 2014; pp. 78–83. [CrossRef]
83. Laubis, K.; Simko, V.; Schuller, A.; Weinhardt, C. Road condition estimation based on heterogeneous extended floating car data. In *Proceedings of the Annual Hawaii International Conference on System Sciences*; IEEE Computer Society: Los Alamitos, CA, USA, 2017; pp. 1582–1591.
84. Youssef, A.; Al-Subaie, N.; El-Sheimy, N.; Elhabiby, M. Accelerometer-based wheel odometer for kinematics determination. *Sensors* **2021**, *21*, 1327. [CrossRef] [PubMed]
85. Li, X.; Chen, R.; Chu, T. A Crowdsourcing Solution for Road Surface Roughness Detection Using Smartphones. In Proceedings of the 27th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2014), Tampa, FL, USA, 8–12 September 2014; pp. 498–502. Available online: https://www.ion.org/publications/abstract.cfm?articleID=12238 (accessed on 2 January 2024).
86. Douangphachanh, V.; Oneyama, H. Estimation of road roughness condition from smartphones under realistic settings. In *Proceedings of the 2013 13th International Conference on ITS Telecommunications*; IEEE: New York, NY, USA, 2013; pp. 433–439. [CrossRef]
87. Douangphachanh, V.; Oneyama, H. A study on the use of smartphones under realistic settings to estimate road roughness condition. *Eurasip J. Wirel. Commun. Netw.* **2014**, *2014*, 114. [CrossRef]
88. Douangphachanh, V.; Oneyama, H. Using Smartphones to Estimate Road Pavement Condition. In *Proceedings of the International Symposium for Next Generation Infrastructure*; University of Wollongong: Wollongong, Australia, 2013. [CrossRef]
89. Kyriakou, C.; Christodoulou, S.E. A low-cost pavement rating system, based on machine learning, utilizing smartphones sensors. *Proc. Inst. Civ. Eng.* **2022**, *175*, 152–159. [CrossRef]
90. Nagaraj, D.D.; Mutz, M.; Venkatesh, S.M.; Riebschlaeger, L.; Werth, D. A Practical Approach for Road Quality Estimation using Smartphone based Inertial Data: IMU data processing pipeline to estimate road quality. In *Proceedings of the International Conference on Machine Learning Technologies*; Association for Computing Machinery (ACM): New York, NY, USA, 2022. [CrossRef]
91. Surblys, V.; Kozłowski, E.; Matijošius, J.; Gołda, P.; Laskowska, A.; Kilikevičius, A. Accelerometer-Based Pavement Classification for Vehicle Dynamics Analysis Using Neural Networks. *Appl. Sci.* **2024**, *14*, 10027. [CrossRef]
92. Gašpar, V. Analyzing road quality using a mobile application. In *Proceedings of the International Symposium on Applied Machine Intelligence and Informatics*; IEEE: New York, NY, USA, 2017; pp. 000317–000320. [CrossRef]

93. Mandal, R.; Dutta, S.; Banerjee, R.; Bhattacharya, S.; Ghosh, R.; Samanta, S.; Saha, T. *City Traffic Speed Characterization Based on City Road Surface Quality*; Springer: Singapore, 2022; pp. 515–524. [CrossRef]
94. Taleqani, A.R.; Bridgelall, R.; Hough, J.; Nygard, K.E. Data Driven Analytics of Road Quality. *Comput. Their Appl.* **2019**, *58*, 454–463. [CrossRef]
95. Kyriakou, C.; Christodoulou, S.E.; Dimitriou, L. Do vehicles sense pavement surface anomalies. In *EC3 Conference 2019*; European Council on Computing in Construction: Sint-Niklaas, Belgium, 2019; Volume 1, pp. 56–64. [CrossRef]
96. Gamage, Y.T.; Thotawaththa, T.; Wijayasiri, A. Identification of Road Surface Anomalies Using Crowdsourced Smartphone Sensor Data. In *Proceedings of the International Conference on Advances in ICT for Emerging Regions*; IEEE: New York, NY, USA, 2022; pp. 118–123. [CrossRef]
97. Kamranfar, P.; Lattanzi, D.; Shehu, A.; Stoffels, S.M. Pavement Distress Recognition via Wavelet-Based Clustering of Smartphone Accelerometer Data. *J. Comput. Civ. Eng.* **2022**, *36*, 04022007. [CrossRef]
98. Wu, T.-H.; Yi, C.-W.; Chan, C.-Y.; Chang, Y.-L.; Tseng, C.-C.; Chung, C.-F. A preliminary study on SPC-crowd pavement indexing. In *Proceedings of the Asia-Pacific Network Operations and Management Symposium*; IEEE: New York, NY, USA, 2015; pp. 336–339. [CrossRef]
99. Kumar, R.; Mukherjee, A.; Singh, V.P. Community Sensor Network for Monitoring Road Roughness Using Smartphones. *J. Comput. Civ. Eng.* **2017**, *31*, 04016059. [CrossRef]
100. Bridgelall, R. Connected Vehicle Approach for Pavement Roughness Evaluation. *J. Infrastruct. Syst.* **2014**, *20*, 04013001. [CrossRef]
101. Laubis, K.; Konstantinov, M.; Simko, V.; Gröschel, A.; Weinhardt, C. Enabling crowdsensing-based road condition monitoring service by intermediary. *Electron. Mark.* **2019**, *29*, 125–140. [CrossRef]
102. Medina, J.R.; Noorvand, H.; Underwood, B.S.; Kaloush, K.E. Statistical Validation of Crowdsourced Pavement Ride Quality Measurements from Smartphones. *J. Comput. Civ. Eng.* **2020**, *34*, 04020009. [CrossRef]
103. Yi, C.-W.; Chuang, Y.-T.; Nian, C.-S. Toward Crowdsourcing-Based Road Pavement Monitoring by Mobile Sensing Technologies. *IEEE Trans. Intell. Transp. Syst.* **2015**, *16*, 1905–1917. [CrossRef]
104. Meocci, M.; Branzi, V.; Sangiovanni, A. An innovative approach for high-performance road pavement monitoring using black box. *J. Civ. Struct. Health Monit.* **2021**, *11*, 485–506. [CrossRef]
105. Bridgelall, R.; Huang, Y.; Zhang, Z.; Deng, F. Precision enhancement of pavement roughness localization with connected vehicles. *Meas. Sci. Technol.* **2016**, *27*, 025012. [CrossRef]
106. Martinelli, A.; Meocci, M.; Dolfi, M.; Branzi, V.; Morosi, S.; Argenti, F.; Berzi, L.; Consumi, T. Road Surface Anomaly Assessment Using Low-Cost Accelerometers: A Machine Learning Approach. *Sensors* **2022**, *22*, 3788. [CrossRef] [PubMed] [PubMed Central]
107. Radopoulou, S.C.; Brilakis, I.; Doycheva, K.; Koch, C. A Framework for Automated Pavement Condition Monitoring. In *Proceedings of the Construction Research Congress*; American Society of Civil Engineers (ASCE): Reston, VA, USA, 2016; pp. 770–779. [CrossRef]
108. Lee, T.; Chun, C.J.; Ryu, S.-K. Detection of Road-Surface Anomalies Using a Smartphone Camera and Accelerometer. *Sensors* **2021**, *21*, 561. [CrossRef] [PubMed]
109. Sprague, W.; Rezazadeh, A.E. Integrating acceleration signal processing and image segmentation for condition assessment of asphalt roads. *Can. J. Civ. Eng.* **2022**, *49*, 1095–1107. [CrossRef]
110. Setiawan, B.D.; Kovacs, M.; Serdült, U.; Kryssanov, V.V. Semantic Segmentation on Smartphone Motion Sensor Data for Road Surface Monitoring. *Procedia Comput. Sci.* **2022**, *204*, 346–353. [CrossRef]
111. Rahmani, M.; Koutsopoulos, H.N.; Ranganathan, A. Requirements and potential of GPS-based floating car data for traffic management: Stockholm case study. In *Proceedings of the IEEE Conference on Intelligent Transportation Systems*; IEEE: New York, NY, USA, 2010; pp. 730–735. [CrossRef]
112. Guo, Y.; Li, B.; Lu, Z.; Zhou, J. A novel method for road network mining from floating car data. *Geo-Spat. Inf. Sci.* **2022**, *25*, 197–211. [CrossRef]
113. Ranacher, P.; Brunauer, R.; Van Der Spek, S.; Reich, S. What is an appropriate temporal sampling rate to record floating car data with a GPS? *ISPRS Int. J. Geo-Inf.* **2016**, *5*, 1. [CrossRef]
114. Ravanelli, R.; Crespi, M. Analysis of the floating car data of turin public transportation system: First results. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2018**, *42*, 579–585. [CrossRef]
115. Chibani, N.E.H.; Sebbak, F.; Cherifi, W.; Senouci, M.R.; Ouchani, S. An Uncertainty-aware Road Anomalies Detection Based on Dempster–Shafer Theory. In *Proceedings of the 2022 First International Conference on Computer Communications and Intelligent Systems (I3CIS)*; IEEE: New York, NY, USA, 2022; pp. 25–30. [CrossRef]
116. Llopis-Castelló, D.; Camacho Torregrosa, F.J.; Romeral-Pérez, F.; Tomás-Martínez, P. Estimation of Pavement Condition Based on Data from Connected and Autonomous Vehicles. *Infrastructures* **2024**, *9*, 188. [CrossRef]
117. Kortmann, F.; Hsu, Y.-C.; Warnecke, A.; Meier, N.; Heger, J.; Funk, B.; Drews, P. Creating Value from in-Vehicle Data: Detecting Road Surfaces and Road Hazards. In *Proceedings of the 2020 IEEE 23rd International Conference on Intelligent Transportation Systems*; IEEE: New York, NY, USA, 2020; pp. 1–6. [CrossRef]

118. Ismail, K.; Muharam, A.; Pratama, M. Design of CAN bus for research applications purpose hybrid electric vehicle using ARM microcontroller. *Energy Procedia* **2015**, *68*, 288–296. [CrossRef]
119. Vogt, M.; Krisp, J.M. Räumliche Lärmanalyse anhand von erweiterten Floating-Car-Daten (xFCD). Spatial Analysis of Noise Using Extended Floating Car Data (xFCD). *KN J. Cartogr. Geogr. Inf.* **2022**, *72*, 73–83. [CrossRef]
120. Harikrishnan, P.M.; Gopi, V.P. Vehicle Vibration Signal Processing for Road Surface Monitoring. *IEEE Sens. J.* **2017**, *17*, 5192–5197. [CrossRef]
121. Allouch, A.; Koubaa, A.; Abbes, T.; Ammar, A. RoadSense: Smartphone Application to Estimate Road Conditions Using Accelerometer and Gyroscope. *IEEE Sens. J.* **2017**, *17*, 4231–4238. [CrossRef]
122. Kyriakou, C.; Christodoulou, S.E. Roadway pavement roughness evaluation based on smart-city principles, vibration sensing and machine learning. In *Proceedings of the European Conference on Computing in Construction*; Springer International Publishing: Cham, Switzerland, 2022. [CrossRef]
123. Brunauer, R.; Schmitzberger, N.; Rehrl, K. Recognizing Spatio-Temporal Traffic Patterns at Intersections Using Self-Organizing Maps. In Proceedings of the 11th ACM SIGSPATIAL International Workshop on Computational Transportation Science (IWCTS'18): Association for Computing Machinery, Seattle, WA, USA, 6 November 2018; pp. 43–52. [CrossRef]
124. Röger, C.; Kalinic, M.; Krisp, J.M. Extracting Densely Covered Areas Within Floating Car Datasets Using Inductive Loop Detector Data. *KN J. Cartogr. Geogr. Inf.* **2021**, *71*, 97–103. [CrossRef]
125. Zeng, J.; Gül, M.; Mei, Q. A computer vision-based method to identify the international roughness index of highway pavements. *J. Infrastruct. Intell. Resil.* **2022**, *1*, 100004. [CrossRef]
126. Rababaah, A.R. A Deep Learning Based Process Model for Crack Detection in Pavement Structures. In Proceedings of the 2022 9th International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 23–25 March 2022; pp. 1–6. [CrossRef]
127. Qu, Z.; Cao, C.; Liu, L.; Zhou, D.-Y. A Deeply Supervised Convolutional Neural Network for Pavement Crack Detection With Multiscale Feature Fusion. *IEEE Trans. Neural Netw.* **2021**, *33*, 4890–4899. [CrossRef] [PubMed]
128. Yang, Y.; Guo, C.; Zuo, C.; Yang, B. A Detection and Classification Method of Asphalt Pavement Crack Based on Vision Transformer. In Proceedings of the 2023 3rd International Conference on Big Data, Artificial Intelligence and Risk Management (ICBAR 2023), Chengdu, China, 24–26 November 2023; pp. 1125–1131. [CrossRef]
129. He, M.; Lau, T.L. A novel network fusing transformer and CNN for road crack segmentation. *IEEE Access* **2024**, *12*, 165610–165625. [CrossRef]
130. Del Serrone, G.; Cantisani, G.; Peluso, P. Blending of Floating Car Data and Point-Based Sensor Data to Deduce Operating Speeds under Different Traffic Flow Conditions. *Eur. Transp. Trasp. Eur.* **2023**, *91*, 5. [CrossRef]
131. Astarita, V.; Giofrè, V.P.; Guido, G.; Vitale, A. The use of adaptive traffic signal systems based on floating car data. *Wirel. Commun. Mob. Comput.* **2017**, *2017*, 4617451. [CrossRef]
132. Cantisani, G.; Del Serrone, G.; Mauro, R.; Peluso, P.; Pompigna, A. From Radar Sensor to Floating Car Data: Evaluating Speed Distribution Heterogeneity on Rural Road Segments Using Non-Parametric Similarity Measures. *Sci* **2024**, *6*, 52. [CrossRef]
133. Cano-Ortiz, S.; Lloret Iglesias, L.; Martinez Ruiz del Árbol, P.; Lastra-González, P.; Castro-Fresno, D. An end-to-end computer vision system based on deep learning for pavement distress detection and quantification. *Constr. Build. Mater.* **2024**, *416*, 135036. [CrossRef]
134. Nafaa, S.; Ashour, K.; Mohamed, R.; Essam, H.; Emad, D.; Elhenawy, M.; Ashqar, H.I.; Hassan, A.A.; Alhadidi, T.I. Automated Pavement Cracks Detection and Classification Using Deep Learning. In Proceedings of the 2024 IEEE 3rd International Conference on Computing and Machine Intelligence (ICMI), Mt. Pleasant, MI, USA, 13–14 April 2024. [CrossRef]
135. Wu, Y.; Yang, W.; Pan, J.; Chen, P. Asphalt pavement crack detection based on multi-scale full convolutional network. *J. Intell. Fuzzy Syst.* **2021**, *40*, 1495–1508. [CrossRef]
136. Dong, Z.; Zhu, G.; Fan, Z.; Liu, J.; Li, H.; Cai, Y.; Huang, H.; Shi, Z.; Ning, W.; Wang, L. Automatic Pavement Crack Detection Based on YOLOv5-AH. In Proceedings of the 2022 12th International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER), Baishan, China, 27–31 July 2022; pp. 426–431. [CrossRef]
137. Mahdy, K.; Zekry, A.; Moussa, M.; Mohamed, A.M.O.; Mahdy, H.A.; Elhabiby, M. Deep Learning Techniques for Efficient Evaluation of Asphalt Pavement Condition. *Mansoura Eng. J.* **2023**, *48*, 10. [CrossRef]
138. Li, H.; Zhang, H.; Zhu, H.; Gao, K.; Liang, H.; Yang, J. Automatic crack detection on concrete and asphalt surfaces using semantic segmentation network with hierarchical Transformer. *Eng. Struct.* **2024**, *307*, 117903. [CrossRef]
139. Ashraf, A.; Sophian, A.; Bawono, A.A. Crack Detection, Classification, and Segmentation on Road Pavement Material Using Multi-Scale Feature Aggregation and Transformer-Based Attention Mechanisms. *Constr. Mater.* **2024**, *4*, 655–675. [CrossRef]
140. Wang, C.; Liu, H.; An, X.; Gong, Z.; Deng, F. SwinCrack: Pavement crack detection using convolutional swin-transformer network. *Digit. Signal Process.* **2024**, *145*, 104297. [CrossRef]

141. Shirvaikar, M.; Souliman, M.I.; Dessouky, S. Estimation of road surface quality using real-time video analysis. In *Real-Time Image Processing and Deep Learning 2023*; Kehtarnavaz, N., Shirvaikar, M.V., Eds.; SPIE: Bellingham, WA, USA, 2023; Volume 12528, p. 1252806. [CrossRef]
142. Huang, Y.-T.; Jahanshahi, M.R.; Shen, F.; Mondal, T.G. Deep Learning-Based Autonomous Road Condition Assessment Leveraging Inexpensive RGB and Depth Sensors and Heterogeneous Data Fusion: Pothole Detection and Quantification. *J. Transp. Eng. Part B Pavements* **2023**, *149*, 04023010. [CrossRef]
143. Astarita, V.; Giofré, V.P.; Festa, D.C.; Guido, G.; Vitale, A. Floating car data adaptive traffic signals: A description of the first real-time experiment with "connected" vehicles. *Electronics* **2020**, *9*, 114. [CrossRef]
144. Kong, X.; Xia, F.; Ning, Z.; Rahim, A.; Cai, Y.; Gao, Z.; Ma, J. Mobility dataset generation for vehicular social networks based on floating car data. *IEEE Trans. Veh. Technol.* **2018**, *67*, 3874–3886. [CrossRef]
145. Stanica, R.; Fiore, M.; Malandrino, F. Offloading floating car data. In Proceedings of the 2013 IEEE 14th International Symposium on a World of Wireless, Mobile and Multimedia Networks, WoWMoM, Madrid, Spain, 4–7 June 2013. [CrossRef]
146. Kessler, L.; Rempe, F.; Bogenberger, K. Multi-Sensor Data Fusion for Accurate Traffic Speed and Travel Time Reconstruction. *Front. Future Transp.* **2021**, *2*, 766951. [CrossRef]
147. Llorca, D.F.; Sotelo, M.A.; Sánchez, S.; Ocana, M.; Rodríguez-Ascariz, J.M.; García-Garrido, M.A. Traffic data collection for floating car data enhancement in V2I networks. *EURASIP J. Adv. Signal Process.* **2010**, *2010*, 719294. [CrossRef]
148. Ayfantopoulou, G.; Militsis, M.N.; Grau, J.M.S.; Basbas, S. Improving Map Matching of Floating Car Data with Artificial Intelligence Techniques. *Information* **2022**, *13*, 508. [CrossRef]
149. Simroth, A.; Zähle, H. Travel time prediction using floating car data applied to logistics planning. *IEEE Trans. Intell. Transp. Syst.* **2011**, *12*, 243–253. [CrossRef]
150. Vázquez, J.J.; Arjona, J.; Linares, M.; Casanovas-Garcia, J. A Comparison of Deep Learning Methods for Urban Traffic Forecasting using Floating Car Data. *Transp. Res. Procedia* **2020**, *47*, 195–202. [CrossRef]
151. Khodabandelou, G.; Kheriji, W.; Selem, F.H. Link traffic speed forecasting using convolutional attention-based gated recurrent unit. *Appl. Intell.* **2021**, *51*, 2331–2352. [CrossRef]
152. Zhang, C.; He, J.; Liu, Z.; Xing, L.; Wang, Y. Travel demand and distance analysis for freefloating car sharing based on deep learning method. *PLoS ONE* **2019**, *14*, e0223973. [CrossRef] [PubMed]
153. Ran, B.; Song, L.; Zhang, J.; Cheng, Y.; Tan, H. Using tensor completion method to achieving better coverage of traffic state estimation from sparse floating car data. *PLoS ONE* **2016**, *11*, e0157420. [CrossRef] [PubMed]
154. Gündüz, G.; Acarman, T. Vehicle travel time estimation using sequence prediction. *Promet Traffic Transp.* **2020**, *32*, 1–12. [CrossRef]
155. Chen, Y.; Chen, C.; Wu, Q.; Ma, J.; Zhang, G.; Milton, J. Spatial-temporal traffic congestion identification and correlation extraction using floating car data. *J. Intell. Transp. Syst. Technol. Plan. Oper.* **2020**, *25*, 263–280. [CrossRef]
156. Altintasi, O.; Tuydes-Yaman, H.; Tuncay, K. Detection of urban traffic patterns from Floating Car Data (FCD). *Transp. Res. Procedia* **2017**, *22*, 382–391. [CrossRef]
157. Li, Q.; Zhang, T.; Yu, Y. Using cloud computing to process intensive floating car data for urban traffic surveillance. *Int. J. Geogr. Inf. Sci.* **2011**, *25*, 1303–1322. [CrossRef]
158. Liu, X.; Liu, K.; Li, M.; Lu, F. A ST-CRF Map-Matching Method for Low-Frequency Floating Car Data. *IEEE Trans. Intell. Transp. Syst.* **2017**, *18*, 1241–1254. [CrossRef]
159. Li, J.; Qin, Q.; Xie, C.; Zhao, Y. Integrated use of spatial and semantic relationships for extracting road networks from floating car data. *Int. J. Appl. Earth Obs. Geoinf.* **2012**, *19*, 238–247. [CrossRef]
160. Rempe, F.; Franeck, P.; Fastenrath, U.; Bogenberger, K. A phase-based smoothing method for accurate traffic speed estimation with floating car data. *Transp. Res. Part C Emerg. Technol.* **2017**, *85*, 644–663. [CrossRef]
161. Cerqueira, V.; Moreira-Matias, L.; Khiari, J.; Van Lint, H. On Evaluating Floating Car Data Quality for Knowledge Discovery. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 3749–3760. [CrossRef]
162. Li, J.; Qin, Q.; Han, J.; Tang, L.-A.; Lei, K.H. Mining trajectory data and geotagged data in social media for road map inference. *Trans. GIS* **2015**, *19*, 1–18. [CrossRef]
163. Liu, J.; Huang, J.; Sun, R.; Yu, H.; Xiao, R. Data Fusion for Multi-Source Sensors Using GA-PSO-BP Neural Network. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 6583–6598. [CrossRef]
164. Kim, G.; Kim, S. A Road Defect Detection System Using Smartphones. *Sensors* **2024**, *24*, 2099. [CrossRef] [PubMed]
165. Alotibi, F.; Abdelhakim, M. Anomaly Detection in Cooperative Adaptive Cruise Control Using Physics Laws and Data Fusion. In *Proceedings of the 2019 IEEE 90th Vehicular Technology Conference*; IEEE: New York, NY, USA, 2019; pp. 1–7. [CrossRef]
166. Yang, L.; Huang, H.P.; Kong, S. A Deep Supervised Pavement Crack Detection Network with Multiscale Feature Fusion and Feature Learning. In Proceedings of the 2023 35th Chinese Control and Decision Conference (CCDC), Yichang, China, 20–22 May 2023; pp. 1002–1007. [CrossRef]
167. Chen, W.; Zhang, X.; Zhao, Q.; Pan, W.; Zhu, J. A Large-Scale Benchmark for Pavement Crack Segmentation. In Proceedings of the 2023 China Automation Congress (CAC), Chongqing, China, 17–19 November 2023; pp. 6166–6170. [CrossRef]

168. Nguyen, P.; Rao, R.; Brown, V.; McConnell, M.; Barendt, N.A.; Zingale, N.C.; Mandal, S.; Kaffashi, F.; Loparo, K.A. A Scalable Pavement Sensing, Data Analytics, and Visualization Platform for Lean Governance in Smart Communities. In Proceedings of the Moratuwa Engineering Research Conference, Moratuwa, Moratuwa, Sri Lanka, 28–30 July 2020; pp. 313–318. [CrossRef]
169. Barabino, B.; Deiana, E.; Mozzoni, S. The quality of public transport service: The 13816 standard and a methodological approach to an Italian case. *Ing. Ferrov.* **2013**, *68*, 475–499.
170. Barabino, B.; Di Francesco, M.; Mozzoni, S. Regularity diagnosis by automatic vehicle location raw data. *Public Transp.* **2013**, *4*, 187–208. [CrossRef]
171. Tilocca, P.; Farris, S.; Angius, S.; Argiolas, R.; Obino, A.; Secchi, S.; Mozzoni, S.; Barabino, B. Managing data and rethinking applications in an innovative mid-sized bus fleet. *Transp. Res. Procedia* **2017**, *25*, 1899–1919. [CrossRef]
172. Barabino, B.; Lai, C.; Casari, C.; Demontis, R.; Mozzoni, S. Rethinking transit time reliability by integrating automated vehicle location data, passenger patterns, and web tools. *IEEE Trans. Intell. Transp. Syst.* **2016**, *18*, 756–766. [CrossRef]
173. Raccagni, S.; Ventura, R.; Barabino, B. Evaluating road crash risk for a mega-event: An application to 2026 Milano-Cortina Winter Olympic games. *Transp. Res. Interdiscip. Perspect.* **2025**, *34*, 101709. [CrossRef]
174. Barabino, B.; Bonera, M.; Maternini, G.; Porcu, F.; Ventura, R. Refining a crash risk framework for urban bus safety assessment: Evidence from Sardinia (Italy). *Reliab. Eng. Syst. Saf.* **2024**, *245*, 110003. [CrossRef]
175. Bonera, M.; Barabino, B.; Yannis, G.; Maternini, G. Network-wide road crash risk screening: A new framework. *Accid. Anal. Prev.* **2024**, *199*, 107502. [CrossRef] [PubMed]