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PERFORMANCE INDICATORS BASED ON VEHICLE TELEMATICS IN FLEET MANAGEMENT: A LITERATURE REVIEW.

INDICADORES DE DESEMPENHO BASEADOS EM TELEMETRIA VEICULAR NA GESTÃO DE FROTAS: UMA REVISÃO DA LITERATURA.

INDICADORES DE DESEMPEÑO BASADOS EN LA TELEMETRÍA VEHICULAR EN LA GESTIÓN DE FLOTAS: UNA REVISIÓN DE LA LITERATURA.

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Abstract

The availability of telematics data expands opportunities to assess fleet performance, but the diversity of applications and measures makes it difficult to establish which indicators are used and what information supports their analysis. This study maps performance indicators associated with vehicle telematics and examines their relationship with the data used in fleet management. A scoping review was conducted and reported in accordance with PRISMA-ScR. Searches covered Scopus, TRID, EBSCO, and SciELO and included publications in Portuguese and English from 2017 to October 17, 2026. Twenty-three studies were included, yielding 15 indicator categories. Seven categories were examined in detail and accounted for 36 of the 51 study–category occurrences (70.6%), covering energy performance, vehicle utilization and condition, vehicle movement, and driver behavior. Fuel consumption and efficiency was the most frequent category, appearing in 43.5% of the sample. The synthesis linked these categories to the telematics data, supplementary records, and derived metrics used in their analysis. Differences in measurement units, information sources, and operational characteristics limit direct comparisons of results across fleets. The review contributes by making explicit the relationships between indicator categories and the information required for their assessment. The findings provide a reference for selecting measures suited to individual operations and identify the need to investigate their combined use and contribution to managerial decisions.

Keywords: Fleet management; Vehicle telematics; Performance indicators; Operational efficiency; Scoping review.

Resumo

A disponibilidade de dados de telemetria amplia as possibilidades de avaliação do desempenho de frotas, mas a diversidade de aplicações e medidas dificulta compreender quais indicadores são utilizados e quais informações sustentam sua análise. Este estudo mapeia os indicadores de desempenho associados à telemetria veicular e examina sua relação com os dados empregados na gestão de frotas. Foi realizada uma revisão de escopo, relatada conforme o PRISMA-ScR, com buscas nas bases Scopus, TRID, EBSCO e SciELO, abrangendo publicações em português e inglês entre 2017

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e 17 de outubro de 2026. Foram incluídos 23 estudos, nos quais se identificaram 15 categorias de indicadores. Sete categorias foram detalhadas e reuniram 36 das 51 ocorrências de categorias nos estudos (70,6%), abrangendo desempenho energético, utilização e condições dos veículos, deslocamento e comportamento dos condutores. Consumo e eficiência de combustível foi a categoria mais frequente, presente em 43,5% da amostra. A síntese relacionou essas categorias aos dados de telemetria, registros complementares e métricas derivadas utilizados em sua análise. Foram observadas diferenças nas unidades de medida, fontes de informação e características operacionais, que limitam a comparação direta dos resultados entre frotas. A contribuição da revisão consiste em explicitar as relações entre as categorias de indicadores e as informações necessárias à sua avaliação. Os achados oferecem uma referência para selecionar medidas compatíveis com cada operação e apontam a necessidade de investigar sua utilização conjunta e sua contribuição para decisões gerenciais.

Palavras-chave: Gestão de frotas; Telemetria veicular; Indicadores de desempenho; Eficiência operacional; Revisão de escopo.

Resumen

La disponibilidad de datos de telemetría amplía las posibilidades de evaluar el desempeño de las flotas, pero la diversidad de aplicaciones y medidas dificulta comprender qué indicadores se utilizan y qué información sustenta su análisis. Este estudio identifica y organiza los indicadores de desempeño asociados a la telemetría vehicular y examina su relación con los datos empleados en la gestión de flotas. Se realizó una revisión de alcance, presentada conforme a PRISMA-ScR, con búsquedas en Scopus, TRID, EBSCO y SciELO, que abarcaron publicaciones en portugués e inglés entre 2017 y el 17 de octubre de 2026. Se incluyeron 23 estudios, en los que se identificaron 15 categorías de indicadores. Siete categorías se examinaron en detalle y reunieron 36 de las 51 apariciones de categorías en los estudios (70,6 %), abarcando desempeño energético, utilización y estado de los vehículos, desplazamiento y comportamiento de los conductores. Consumo y eficiencia de combustible fue la categoría más frecuente, presente en el 43,5 % de la muestra. La síntesis relacionó estas categorías con los datos de telemetría, registros complementarios y métricas derivadas utilizados en su análisis. Se observaron diferencias en las unidades de medida, fuentes de información y características operativas que limitan la comparación directa de resultados entre flotas. La revisión contribuye a explicitar las relaciones entre las categorías de indicadores y la información necesaria para evaluarlas. Los resultados ofrecen una referencia para seleccionar medidas adecuadas a cada operación y señalan la necesidad de investigar su uso conjunto y su contribución a las decisiones de gestión.

Palabras clave: Gestión de flotas; Telemetría vehicular; Indicadores de desempeño; Eficiencia operativa; Revisión de alcance.

1. Introduction

In the transport and logistics sectors, fleet management plays an important role in organizations that rely on vehicles to carry out their activities. It seeks to ensure efficient, safe, and economical vehicle use, reducing costs and increasing productivity (ESPÍRITO SANTO, 2024). To make the best use of vehicles and available resources, fleet management involves resource planning, control, and monitoring.

These aspects are generally monitored through performance indicators and the assessment of operational results. Performance indicators translate aspects of organizational operations into measurable information, supporting the monitoring, assessment, and improvement of fleet management (SOARES et al., 2022). However,

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the quality of these analyses depends directly on the reliability and quality of the underlying data, making technological tools increasingly essential and relevant to operations management.

Telematics enables real-time vehicle monitoring, including location, speed, and other operational variables, contributing to fleet safety, efficiency, and proactive management (SILVA and SANTOS, 2024).

It is important to understand how telematics data can be and are used to develop and monitor performance indicators. Although these data are available, they tend to accumulate in large databases, making a clearer understanding of what each value represents essential to extracting useful information. The scientific literature describes different applications of this technology, but identifying which indicators are actually used and which data are required for their analysis remains a relevant question.

This scoping review aims to map the categories of performance indicators associated with vehicle telematics in fleet management and identify the data used in their development and analysis. The synthesis links the identified categories to their respective information sources, helping to clarify which aspects of performance are monitored in the studies and what information is required to assess them.

2. Methods

A scoping review is an approach to evidence synthesis that systematically identifies and maps the scientific literature on a topic, enabling the identification of concepts, study types, research gaps, and areas requiring further investigation (Peters et al., 2021).

The identification and selection of studies were reported in accordance with the PRISMA 2020 statement (Page et al., 2021), which guided the reporting of the review process.

This study is exploratory and descriptive, drawing on a scoping review to map performance indicators associated with vehicle telematics in fleet management. The analysis combines qualitative categorization of the indicators and their data sources with a quantitative description of their frequency across the included studies. This approach makes it possible to examine both what is measured and which information

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supports the assessment, while accounting for differences in fleet types, operational contexts, and measurement methods.

2.1 Eligibility criteria

The eligibility criteria covered publications from 2017 to October 17, 2026, written in Portuguese or English. Eligible publication types were limited to scientific journal articles, full conference papers, and academic theses or dissertations. Other formats, including extended abstracts, undergraduate final projects, book chapters, and general-interest publications, were excluded.

For the purposes of this review, a vehicle fleet was defined as a group of vehicles or mobile equipment operated or managed within a coordinated operational context. This definition was not restricted to road transport and also covered applications involving heavy-duty vehicles, commercial vehicles, tractors, and mobile equipment used in mining and other operational activities. The central requirement was that the vehicles or equipment were examined as part of a fleet operation, rather than as isolated technological units.

In addition to these formal requirements, the relevance of the content was assessed. Only studies that treated a vehicle fleet as the unit of analysis and used, or at least discussed, telematics data or other vehicle monitoring data relevant to fleet performance were considered. Studies were also required to calculate, monitor, compare, or analyze at least one indicator or variable related to operational performance or productivity.

The eligibility criteria presented in Table 03 established the formal and thematic requirements for a study to be considered within the scope of the review. In addition, a structured assessment instrument (P1–P8) was applied during the final selection process to examine the thematic relevance and information sufficiency of the retrieved studies. This instrument was used to determine whether the information provided was sufficiently explicit to support the identification of performance indicators and their corresponding data sources. Therefore, the eligibility criteria and the assessment instrument served complementary but distinct purposes in the study selection process.

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2.2 Search strategy

The online search was conducted on October 17, 2026, in Scopus, SciELO (Scientific Electronic Library Online), TRID (Transport Research International Documentation), and EBSCO (Academic Search Ultimate).

The searches were conducted in two stages. The first consisted of a broad search using Boolean search strings that combined the main terms related to the topic, without additional restrictions, to retrieve as many potentially relevant publications as possible. The second consisted of a supplementary search using refined Boolean search strings that included terms related to performance, efficiency, and productivity, narrowing the results to studies more closely aligned with the review objective.

Table 01 – Search strategies and results

Database	Search	Search strategy	Results
Scopus	Broad	TITLE-ABS-KEY (fleet AND (telematics OR telemetry OR "vehicle tracking" OR GPS))	2002
Scopus	Supplementary	TITLE-ABS-KEY (fleet AND (telematics OR telemetry OR "vehicle tracking" OR GPS) AND (performance OR efficiency OR productivity))	732
TRID	Broad	fleet AND (telematics OR telemetry OR "vehicle tracking" OR GPS)	1447
TRID	Supplementary	(telematics OR telemetry OR "vehicle tracking" OR GPS) AND ("fleet management" OR "fleet performance" OR "operational efficiency" OR "performance indicator*")	906
EBSCO	Broad	fleet AND (telematics OR telemetry OR "vehicle tracking" OR GPS)	461
EBSCO	Supplementary	fleet AND (telematics OR telemetry OR "vehicle tracking" OR GPS) AND (performance OR efficiency OR productivity)	156
SciELO	Comprehensive	(telemetria OR telematic OR GPS OR rastreamento) AND (frotas OR frota OR fleet OR veículos)	22
Total	—	—	5726

Source: Prepared by the author (2026).

Both stages accounted for the specific features of each database. Table 01 presents the broad and supplementary search strategies used in each database, together with the Boolean operators and the corresponding results.

Following the initial searches, language filters (Portuguese and English) and publication period filters (2017–2026) were applied in each database, as specified in the eligibility criteria, using the same search strategies presented in Table 01. Table 02 presents the results after these filters were applied.

Table 02 – Applied filters and results

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Database	Search	Language	Period	Results
Scopus	Broad	English and Portuguese	2017–2026	1050
Scopus	Supplementary	English and Portuguese	2017–2026	442
TRID	Broad	English and Portuguese	2017–2026	307
TRID	Supplementary	English and Portuguese	2017–2026	161
EBSCO	Broad	English and Portuguese	2017–2026	281
EBSCO	Supplementary	English and Portuguese	2017–2026	108
SciELO	Comprehensive	English and Portuguese	2017–2026	14
Total	—	—	—	**2363**

Source: Prepared by the author (2026).

Metadata from the retrieved records were extracted into spreadsheets, and the records were then submitted to the study selection process.

2.3 Study selection

Initially, 2,363 records were identified across the four databases. Before the screening stage, 1,150 records were removed for three distinct reasons: 948 due to duplicate titles, 114 because the publication type was inappropriate, and 88 for being irrelevant to the review topic, based on a preliminary relevance assessment.

Duplicates were identified manually using Microsoft Excel by comparing the titles and abstracts of the records. After standardizing this information, duplicate titles were highlighted and removed individually, with the duplication confirmed for each study. Records deemed potentially irrelevant were first evaluated with the assistance of the artificial intelligence tool ChatGPT, using an Excel spreadsheet that indicated whether each study was relevant to the review. Subsequently, each record was read and selected manually, then reclassified by the researcher to ensure the reliability of the process. Thus, the preliminary relevance assessment involved the use of artificial intelligence tools, followed by a manual verification conducted by the researcher.

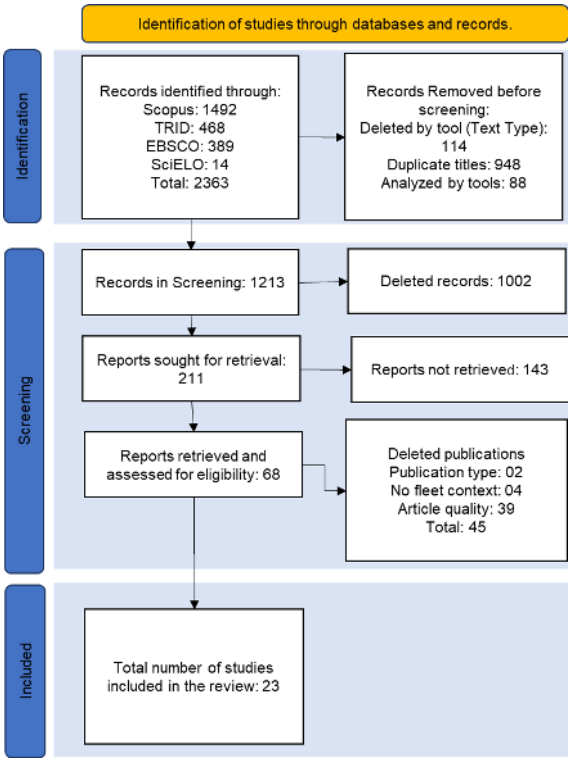
Following these exclusions, 1,213 records remained for the screening stage.

Figure 01 – PRISMA flow diagram

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Source: Prepared by the author (2026).

The eligibility criteria applied in the final screening stage are detailed in Table 03.

Table 03 – Eligibility criteria

Criterion	**Inclusion criteria**	**Exclusion criteria**
Publication period and language	Publications from 2017 to October 17, 2026, written in Portuguese or English.	Publications outside the defined period or in other languages.
Publication type	Scientific journal articles, full conference papers, and academic theses or dissertations.	Extended abstracts, undergraduate final projects, book chapters, and general-interest publications.
Fleet context	Studies that examine vehicle fleets or transport operations involving vehicles as the unit of analysis.	Studies not addressing fleet operations or focusing exclusively on isolated technological applications without a fleet-management context.
Data sources	Studies using or discussing telematics data or other relevant vehicle monitoring data related to fleet performance.	Studies that do not address telematics or relevant vehicle monitoring data.
Performance indicators	Studies calculating, monitoring, comparing, or	Studies that do not identify, calculate, monitor, compare, or analyze any

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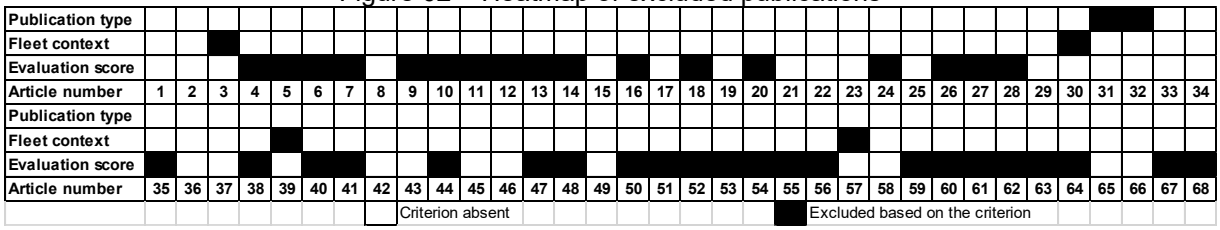
	analyzing at least one indicator or variable related to operational performance or productivity.	relevant performance indicator or operational variable

Source: Prepared by the author (2026).

To provide a detailed account of the final selection stage, Figure 02 presents the distribution of the 68 assessed studies according to three criteria: publication type, fleet context, and the assessment score. The heatmap identifies 39 studies that did not meet the required score threshold, two studies excluded due to publication type, and four studies excluded because they did not address vehicle fleets as the unit of analysis. These exclusions resulted in a final sample of 23 studies

A heatmap can be understood as a rectangular grid in which each cell is shaded according to a color scale representing the value of the corresponding element in the data matrix, making patterns of similarity between rows and columns immediately identifiable (WILKINSO N; FRIENDLY, 2009).

Figure 02 – Heatmap of excluded publications



Source: Prepared by the author (2026).

The final selection classification was based on an assessment of thematic relevance and the sufficiency of information, and the process is explained in Section 2.3.1.

2.3.1 Assessment of thematic relevance and information sufficiency

The final screening stage included an assessment of thematic relevance and information sufficiency, using a structured instrument applied individually to each study. The purpose of this assessment was to determine whether the publications addressed the subject of the review and provided sufficient information to identify performance indicators associated with vehicle telematics and the data used in their analysis. The instrument comprised eight questions (P1 to P8), organized into main assessment criteria and complementary criteria. The first five questions (P1 to P5) were scored on a scale from 0 to 2: 0 indicated that the study did not address the criterion or provided

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no relevant evidence; 1 indicated partial or indirect evidence, or insufficient detail; and 2 indicated that the criterion was clearly addressed, with explicit and relevant information. The sum of P1 to P5 established a maximum initial score of 10 points. The complementary questions (P6 to P8) were used to examine the explicit identification of indicators, the relationship between telematics data and indicators, and the managerial relevance of the findings. Their scoring procedure is described below.

Table 04 – Main criteria for assessing thematic relevance and information sufficiency

Question	**Assessment criterion**
P1 – Performance indicators	Does the study identify or analyze fleet performance indicators or variables?
P2 – Telematics data	Do the data used come from telematics or relevant vehicle monitoring sources?
P3 – Operational application	Does the study explain how the data or indicators are defined, calculated, monitored, compared, or used?
P4 – Efficiency and productivity	Does the study address costs, fuel, vehicle utilization, maintenance, safety, productivity, or another relevant operational dimension?
P5 – Contribution to the review	Does the study contribute to identifying indicators, data sources, managerial applications, research gaps, or research opportunities?

Source: Prepared by the author (2026).

Three complementary questions (P6 to P8) were included to examine aspects that were not fully captured by the main assessment criteria. These questions focused on the explicit identification of performance indicators, the possibility of establishing a relationship between the telematics data and the indicators analyzed, and the managerial relevance of the reported findings. Unlike the main questions, the complementary criteria were scored using a reversed scale: 0 indicated that the criterion was fully met, resulting in no penalty; 1 indicated partial compliance, resulting in a partial penalty; and 2 indicated that the criterion was not met, resulting in the maximum penalty. These criteria were intended to examine the extent to which the information presented in each study could be directly extracted and used in the review synthesis. Table 05 presents the complementary questions.

Table 05 – Complementary criteria for information sufficiency

Question	**Assessment criterion**
P6 – Explicit identification of indicators	Does the article identify performance indicators or variables that can be extracted for the review?
P7 – Relationship between data and indicators	Can the telematics or monitoring data used to analyze each indicator be identified?
P8 – Managerial relevance	Do the results contribute to decisions concerning planning, control, maintenance, cost reduction, or productivity?

Source: Prepared by the author (2026).

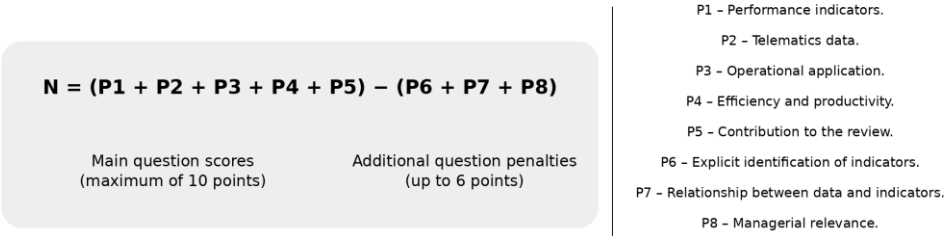
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The final score for each study therefore corresponded to the sum of P1 to P5 (a maximum of 10 points) minus the penalties accumulated in P6 to P8 (a maximum of 6 points), yielding a possible range from −6 to 10 points. Each article's score was calculated using the formula shown in Figure 03.

Figure 03 – Quality assessment formula



Source: Prepared by the author (2026).

Based on the resulting scores, the studies were grouped into three categories according to their level of compliance with the thematic and informational criteria established for the review: insufficient information, for scores of 4 or below; partially sufficient information, for scores from 5 to 9; and full compliance with the assessment criteria, for a score of 10. This classification was used to distinguish studies according to the extent to which they provided the information required for the proposed synthesis, as presented in Table 06.

Table 06 – Classification of studies according to compliance with assessment criteria

Classification	Score range	Number of articles
Insufficient information	≤ 4	29
Partially sufficient information	> 4 e ≤ 9	10
Full compliance with the criteria	≥ 10	29
Classification		68

Source: Prepared by the author (2026).

Note: The 29 studies achieving the maximum score were subsequently examined against the publication type and fleet context eligibility criteria. Six studies were excluded at this stage, leaving 23 studies for the final review sample.

Of the 68 studies assessed during the final screening stage, 29 were classified as providing insufficient information and 10 as providing partially sufficient information, resulting in 39 studies that did not meet the established threshold for inclusion. Additionally, two studies were excluded because they did not meet the publication-type criteria, and four because they did not address vehicle fleets as the unit of analysis.

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The remaining 23 studies met the established inclusion requirements and comprised the final sample of this review.

The 10-point cutoff is based on the review's informational requirements rather than on methodological quality. It ensured that the selected studies fully met the key thematic and informational criteria—without additional penalties—and provided sufficiently explicit information to identify, categorize, and analyze telematics-based performance indicators, as well as their respective data sources.

This threshold was applied to ensure that the review prioritized studies from which information could be directly extracted and systematically organized in alignment with the research objectives. Studies with lower scores were not necessarily methodologically flawed; rather, they simply did not fully meet the specific thematic and informational requirements of this review. Consequently, the selection of the 23 studies reflects their compliance with the predefined evaluation criteria and their potential contribution to the proposed synthesis, rather than a ranking of their overall scientific or methodological quality.

2.4 Procedures for analyzing the included studies

After selecting the 23 studies, the full texts were read and a brief summary of the central theme of each was prepared, with the aim of confirming its suitability to the established inclusion criteria.

NotebookLM was used as a tool to support the organization and protection of information from the included studies. The 23 articles, in PDF format, were uploaded to the platform to assist in characterizing the studies, identifying indicator categories, and specifying the data necessary for analysis.

In order to ensure the accuracy of the information, a manual check of the results generated by the tool was carried out. It was verified that the content presented was consistent with the prepared summaries and, furthermore, that the sources indicated by NotebookLM corresponded to the information extracted from each study.

2.4.1 Characteristics of the included studies

The studies were analyzed in terms of article identification using codes A01 to A23, authorship, publication year, country where the study was conducted, fleet type, main objective, and methodology.

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2.4.2 Identification and categorization of performance indicators

Each included study was analyzed individually to identify, standardize, and group performance indicators related to telematics and fleet management. For each indicator identified, the studies in which it was actually used, analyzed, calculated, or monitored were counted. The indicators were then organized according to their occurrence in the documentary sample, recording the number of corresponding studies and their percentage frequencies. Figure 04 presents the frequency calculation.

Figure 04 – Percentage frequency formula

$$F\,(\%) = \frac{\text{Number of articles with the indicator}}{23} \times 100$$

Source: Prepared by the author (2026).

Equivalent terms were grouped while preserving conceptual distinctions. Raw telematics data that were not analyzed as performance indicators were excluded.

For frequency calculations, each study was counted only once within each indicator category, regardless of the number of specific measures identified in that category. Thus, each study–category association represented one occurrence, and a study could contribute to more than one category when applicable. To ensure traceability, the studies were identified by codes A01 to A23, which were used to link the extracted information to the corresponding categories in Table 08 and to the telematics data, supplementary records, and derived metrics presented in Table 09.

2.4.3 Selection of indicator categories for detailed analysis

The categories were ranked according to the number of studies in which they occurred. For the descriptive analysis, seven categories were selected based on their frequency distribution. Each association between a study and a category was counted as one occurrence, yielding 51 occurrences in total. The seven categories examined in detail accounted for 36 occurrences, equivalent to 70.6% of the total, following an adaptation of the 70/30 Pareto Principle (Atlassian, 2026).

This selection was intended to guide the detailed examination of the categories most frequently represented in the reviewed literature. It should not be interpreted as a ranking of managerial importance, operational impact, or effectiveness, since frequency of occurrence in the literature does not necessarily reflect the practical

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relevance of an indicator in fleet management. At the cutoff point, driver behavior and driving aggressiveness, distance traveled, and fleet productivity and volume handled had the same frequency, with three studies each. Driver behavior and driving aggressiveness was retained for detailed analysis among these categories with tied frequencies.

2.4.4 Identification and classification of telematics data

Finally, the studies were analyzed to identify the telematics data actually used for each indicator selected through the Pareto Principle, producing a synthesis of the most frequently used data.

3. Results and Discussion

3.1 Study characteristics

Table 07 presents the characteristics of the included studies, covering their codes, authorship, country of origin, fleet type, research objective, and methodological approach.

Table 07 – Characteristics of the studies included in the review

No.	Author	Country	Fleet	Objective	Methodology
A01	Abu-Abed and Ivanov (2021)	Russia	Mining equipment (trucks simulated on virtual routes)	Assess the use of the open-source SUMO simulation software integrated with InfluxDB and Grafana for monitoring and managing mining fleet logistics without physical hardware costs.	Computational modeling and simulation with a time-series database.
A02	Costagliola et al. (2025)	Italy	Heavy-duty trucks / Euro 6 road tractor units (5 N3 vehicles)	Assess the real-world effect of high-performance fuel additives on diesel consumption in Euro 6 road tractor units under actual operating conditions.	Empirical experimental study in an actual fleet (pre- and post-intervention design).
A03	Oliveira et al. (2023)	Brazil	Mining equipment (Caterpillar and Komatsu off-highway trucks)	Develop telematics-based dashboards and average-speed management tools to optimize ore and waste transport in open-pit mines.	Quantitative empirical case study with inferential statistical analysis.
A04	Wyrwa and Stryhunivska (2026)	Poland	Commercial vehicles and heavy-duty trucks (20 delivery vehicles and four 40-tonne trucks)	Assess fuel consumption efficiency in a commercial logistics fleet and compare the consistency of different data sources (CAN bus, fuel cards, and tank measurements).	Quantitative analytical case study using Pareto analysis and error metrics.

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A05	Melkonyan et al. (2026)	Bulgaria	Fleet of tractor units and semitrailers	Assess the economic and operational effects of integrating BLE sensors and LTE trackers to automate trailer coupling in the TMS.	Quantitative empirical case study (before-and-after design with a baseline).
A06	Viscenheski et al. (2026)	Brazil	Heavy-duty trucks (1,117 Euro 6 trucks)	Characterize powertrain component failure profiles by combining continuous LVD telematics and warranty records through unsupervised learning.	Applied research using machine learning (Fuzzy C-Means and Fuzzy SOM).
A07	Lee et al. (2026)	South Korea	Earthmoving equipment (excavators, tractors, and dump trucks)	Develop an earthmoving fleet monitoring system based exclusively on GNSS data without relying on proprietary onboard sensors.	Methodological and technological research validated at construction sites.
A08	Anghelache et al. (2023)	Romania	Commercial vehicles (28 freight and delivery vehicles on 427 routes)	Develop and validate the iRoute adaptive route planning algorithm using historical GPS trajectories and driver behavior.	Software development and empirical field validation.
A09	Shakenov et al. (2026)	Kazakhstan	Mining equipment (12 Caterpillar 785D off-highway trucks)	Assess the effects of maintenance and repairs to mining road surfaces on fuel consumption, cycle time, and mechanical stress.	Quasi-experimental field study using a difference-in-differences model.
A10	Farahpoor et al. (2024)	Spain	Industrial vehicles and commercial mining and construction fleets	Propose the IDHMS architecture for intelligent dispatching, real-time communication, and vehicle health monitoring across different makes.	IoT/cloud technology architecture proposal and integration testing.
A11	Szcześniak and Gorzelańczyk (2024)	Poland	Heavy-duty trucks (55 Euro 6 tractor units used in international transport)	Analyze reductions in operational costs and fuel consumption through telematics monitoring of driving parameters and truck models.	Quantitative empirical study using multiple linear regression.
A12	Aldossary et al. (2026)	Saudi Arabia	Electric vehicles (commercial EV fleets / batteries and electric motors)	Develop the quantum-temporal Q-TRACNet network to estimate remaining useful life (RUL) and state of health (SoH) in electric vehicle fleets.	Applied research using quantum-temporal deep learning (Q-TRACNet).
A13	Yu et al. (2026)	China	Heavy-duty trucks (GPS trajectory data for urban and regional freight)	Reconstruct trip chains and categorize heavy-duty truck operational behavior using large-scale GPS trajectory data.	Quantitative statistical study using DBSCAN and K-means clustering.
A14	Torres-Espinoza et al. (2026)	Peru	Personnel transport vehicles (corporate van/minibus fleets)	Assess the usability and effectiveness of the MoviGestion architecture integrated with a conversational AI chatbot to	User-centered design (Lean UX) and empirical usability testing (SUS).

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				automate personnel transport management.	
A15	Sharma et al. (2026)	India	Connected commercial vehicles and road transport fleets	Develop the Middle-Order Ranking (MOR) framework based on the median and absolute deviation for vehicle health ranking and route assignment.	Computational simulation study and robust statistical analysis.
A16	Botelho et al. (2026)	Brazil	Passenger and light commercial vehicles (hybrid and electric vehicle trips)	Propose an environmentally unbiased K-means clustering framework for fair comparison of fuel efficiency across driving contexts.	Quantitative study using unsupervised machine learning (K-means).
A17	Priya et al. (2019)	India	Commercial road freight and container transport vehicles	Develop a three-layer fleet resource management system (IoT, Web, Data) to prevent cargo theft and control weight and fuel.	Development of an IoT hardware and software engineering prototype.
A18	Nagy et al. (2021)	Hungary	Light vehicles / passenger cars (gasoline and diesel engines in an AUDI fleet)	Develop a rapid method to assess lubricating oil degradation by correlating vehicle tracking data with FT-IR spectroscopy and PCA.	Field experimental study and multivariate chemometric analysis (PCA).
A19	Salhieh et al. (2021)	Jordan	Light commercial vehicles for urban last-mile distribution (40 vehicles)	Assess the causal effect of installing tracking and routing systems on the technical efficiency and operational costs of distribution fleets.	Controlled field experiment (RCT) and data envelopment analysis (DEA).
A20	D'Agostino et al. (2024)	Italy	Heavy- and medium-duty trucks (Iveco Eurocargo Euro VI trucks)	Characterize heavy-duty commercial vehicle operating missions using summary metrics of energy consumption (kWh/km) and engine behavior.	Descriptive exploratory study using Signal Logger telematics data.
A21	Stancel and Surugiu (2017)	Romania	Heavy goods vehicles (trucks and road platoons on transport corridors)	Propose a technological framework based on onboard units (OBUs) and V2V/V2I communication for emissions monitoring and platoon formation.	Architectural model proposal and traffic dynamics simulation.
A22	Ettousy, Zyane, and Jamiri (2025)	Morocco	Commercial vehicles and agricultural trucks (22 agro-industrial vehicles)	Optimize agricultural transport logistics by analyzing telematics and GPS tracking data to reduce fuel consumption and idle time.	Quantitative empirical case study using time-series analysis.
A23	Penna et al. (2017)	India	Public transport buses and urban operational vehicles	Develop a low-cost fuel monitoring and GPS odometer system using Arduino and GSM/GPRS for public transport.	Development of an engineering prototype and field functionality testing.

Source: Prepared by the author (2026), based on the selected studies.

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The geographical distribution of the articles shows that research has been conducted in different regions of the world. This demonstrates the international nature of the topic and suggests that vehicle tracking, telematics, and monitoring technologies are applied across different economic and operational settings.

The fleets investigated were predominantly associated with road freight transport, particularly heavy-duty trucks, tractor units, passenger vehicles, and semitrailers. Some studies also addressed bus fleets, passenger vehicles, electric vehicles, tractors, and earthmoving equipment, demonstrating the breadth of applications of the technology analyzed.

The research objectives show a concentration on technological solutions to improve operational fleet control, energy efficiency, operational safety, fuel consumption, and maintenance management. Other studies used telematics and tracking data to characterize driver behavior, optimize routes, identify travel patterns, and anticipate potential mechanical failures.

The variety of methodologies indicates that the literature analyzed includes both investigations aimed at understanding operational phenomena and studies focused on designing, implementing, or validating technological solutions.

The study characteristics reveal research focused on integrating data analysis, fleet management, and digital technologies. However, the diversity of applications and approaches also highlights the need to organize the indicators used to assess their results. Identifying the indicators and analyzing how frequently they appear in the studies is therefore essential to understanding which dimensions of operational efficiency are most often measured in the literature and which offer opportunities for further investigation.

3.2 Identified indicators

Fifteen categories of performance indicators associated with tracking technology, vehicle monitoring, and telematics were identified. Table 08 presents their distribution.

Table 08 – Identified indicators

Indicator	Studies	Frequência

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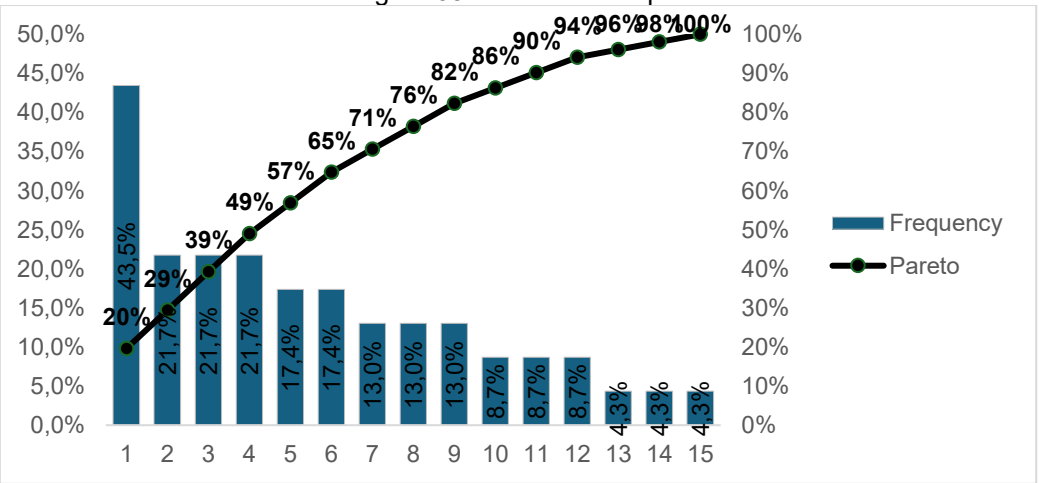
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Fuel consumption and efficiency	10 (A02, A03, A04, A09, A11, A16, A17, A20, A22, A23)	43,5%
Trip duration and allocation of driving time	5 (A07, A08, A11, A16, A22)	21,7%
Vehicle health, diagnostics, and predictive maintenance	5 (A06, A09, A10, A12, A18)	21,7%
Inactivity and engine idling	5 (A05, A07, A13, A17, A22)	21,7%
Route accuracy, tracking, and route compliance	4 (A05, A13, A14, A15)	17,4%
Speed and movement dynamics	4 (A01, A03, A09, A21)	17,4%
Driver behavior and driving aggressiveness	3 (A11, A12, A20)	13,0%
Distance traveled	3 (A02, A08, A19)	13,0%
Fleet productivity and volume handled	3 (A03, A07, A10)	13,0%
Administrative efficiency and incident response	2 (A05, A14)	8,7%
Pollutant emissions and carbon footprint	2 (A03, A21)	8,7%
Duration and number of operating cycles	2 (A07, A09)	8,7%
Payload and transported weight	1 (A17)	4,3%
Sensor data reliability and stability	1 (A15)	4,3%
Overall relative fleet efficiency (DEA score)	1 (A19)	4,3%

Source: Prepared by the author (2026), based on the selected studies.

Figure 05 presents the categories in descending order of frequency. The bars represent the frequencies, calculated according to Figure 04, while the Pareto line indicates the cumulative percentage of the 51 identified occurrences.

Figure 05 – Pareto Principle



Source: Prepared by the author (2026).

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Based on the frequency distribution shown in Figure 05, seven categories were selected for detailed descriptive analysis: fuel consumption and efficiency; trip duration and allocation of driving time; vehicle health, diagnostics, and predictive maintenance; inactivity and engine idling; route accuracy, tracking, and route compliance; speed and movement dynamics; and driver behavior and driving aggressiveness. This selection reflects the distribution of categories across the reviewed studies and does not establish their relative managerial importance or operational priority.

The prioritization of the Driver Behavior and Driving Aggressiveness indicator, over indicators such as distance traveled and fleet productivity or volume moved, is justified by its direct and measurable impact on fuel consumption, operational safety and vehicle integrity. Aggressive driving—characterized by speeding, harsh acceleration, and rapid braking—can reduce fuel efficiency by approximately 15% to 30% on highways and by 10% to 40% in urban conditions, with frequent stops and starts (UNITED STATES DEPARTMENT OF ENERGY, 2026).

Therefore, monitoring this indicator allows for the identification of risk patterns, guiding training and feedback actions for drivers, and promoting safer, more economical, and sustainable driving. In addition to contributing to reduced operating costs, improved driving behavior reduces the likelihood of accidents, premature wear of vehicle components, and emissions associated with fleet operation.

3.3 Indicators and telematics data

Table 9 presents the relationship between the identified performance indicators and the respective telemetry data used by the studies as sources of information for their construction and analysis.

Table 09 – Telematics data, supplementary records, and derived metrics associated with indicator categories

Indicator	Data, supplementary records, and derived metrics
Fuel consumption and efficiency	GPS(Global Positioning System)/GNSS(Global Navigation Satellite System) coordinates and digital odometer – (A02),(A03) (A04), (A11), (A16), (A22), (A23)
	CAN bus(Controller Area Network)/OBD(On-Board Diagnostics II)-II parameters (injection/flow/volume) – (A02), (A04), (A20)
	Analog fuel tank level readings – (A04), (A17), (A22), (A23)
	Engine speed (RPM(Revolutions Per Minute) and speed ranges – (A11), (A16), (A20)
	Fuel cards – (A04)
	Consumption per cycle (L/cycle) and fuel intensity (L/(t·km)) – (A09)
	BSFC score and kWh/km ratio – (A20)

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Trip duration and allocation of driving time	Start/end timestamps and ignition timestamps (key-on/key-off) – (A07), (A08), (A16), (A22)
	GPS/GNSS location coordinates – (A07), (A08), (A22)
	Accumulated active driving time x2 in seconds – (A11)
Vehicle health, diagnostics, and predictive maintenance	Tire pressure and temperature (TPMS(Tire Pressure Monitoring System) and brake use – (A10)
	Engine temperature and coolant/oil parameters – (A10), (A12), (A18)
	Electrical voltage and current signals and battery/motor signals – (A10), (A12)
	Acceleration and RMS (Root Mean Square) vibration (g) – (A09), (A12)
	LVD powertrain signals and warranty orders – (A06)
	Suspension mechanical stress proxy – (A09)
	Oil FT-IR spectroscopy – (A18)
Inactivity and engine idling	GPS stop coordinates and movement thresholds – (A07), (A13) e (A17)
	Ignition signals (engine running/engine off) and idling logs – (A17), (A22)
	Coupling timestamps and BLE(Bluetooth Low Energy)/LTE(presence signals – (A05)
Route accuracy, tracking, and route compliance	Continuous GPS/GNSS coordinates and geographical trajectories – (A13), (A14), (A15)
	BLE beacon signals on the trailer and LTE trackers on the tractor unit – (A05)
	MOR framework and MORS (Middle-Order Routing Score), cross-referenced with maps – (A15)
Speed and movement dynamics	Instantaneous speed (km/h) and short-interval telematics records – (A03), (A09), (A21)
	Instantaneous acceleration (m/s²) and steering angle in degrees – (A01)
Driver behavior and driving aggressiveness	Rapid acceleration and harsh braking events – (A11), (A12), (A20)
	Cruise control and retarder use duration – (A11)
	DAI(Driving Aggressiveness Index) index with jerk weighting – (A12)
	RPA(Relative Positive Acceleration)and RPPTv(Relative Positive Percentage Torque Variation) indices – (A20)

Source: Prepared by the author (2026), based on the selected studies.

Note: The table distinguishes primary data sources, supplementary records, and derived performance metrics. Primary data include measurements collected through vehicle monitoring systems and sensors, whereas derived metrics result from calculations or combinations of these measurements. Measurement units are presented where specified in the original studies. Abbreviations are defined at their first occurrence or in the table notes.

MOR: Middle-Order Ranking, a statistical and decision-making framework based on IoT sensor data. MORS: Middle-Order Routing Score, the main metric associated with the MOR framework, used to support fleet and route-related decisions. The framework is described in Sharma et al. (2026).

Table 09 links the seven selected categories to the telematics data, supplementary records, and derived metrics used in the studies. This organization identifies the information associated with the development and interpretation of indicators in each category.

The information comprises measurements obtained through vehicle monitoring systems, records from other sources, and metrics calculated from these data. The same information may contribute to different indicator categories. The number of rows

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in the table therefore represents the associations presented and depends on how they were grouped for presentation.

The comparison between studies shows that similar categories can encompass indicators with different units and purposes. For energy performance, for example, the discussion presents measures related to distance traveled, payload, and engine operation. This diversity requires consideration of each indicator's definition, measurement unit, and operational characteristics before comparing results across fleets. Grouping indicators into categories therefore helps organize the literature, but managerial application requires identifying the specific measure used in each study.

Table 09 also shows that information is shared across different categories. Location, speed, and time records can contribute to monitoring vehicle movements, trip duration, and periods of inactivity. This relationship suggests that monitoring plans can jointly consider the available data and the decisions they are intended to support. This review contributes by organizing these associations, providing a basis for selecting indicators and identifying the information required for their use in different fleet management settings.

3.4 Discussion

The operational implications discussed in this section are interpreted according to the type of evidence reported in each study. Empirical evidence refers to findings obtained from actual operational data or practical applications, whereas simulation-based evidence refers to results generated through computational models or simulated scenarios. Propositive evidence refers to applications, relationships, or potential benefits suggested by the authors but not empirically demonstrated or simulated in the study. This distinction is intended to clarify the evidential basis of the reported findings and avoid interpreting proposed applications as demonstrated operational improvements.

Fuel consumption and efficiency are relevant to assessing fleet operational performance because they relate energy resources to distance traveled and vehicle operating conditions. These indicators can be developed by integrating GPS, odometer, CAN bus, and fuel level sensor data. Costagliola et al. (2025) demonstrate this integration through a GPS system connected to the engine control unit via OBD.

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Wyrwa and Stryhunivska (2026) identify CAN parameters as a primary source for fuel consumption calculations because of the greater consistency of the records, while noting that fuel level sensors can be affected by vehicle inclination and fuel movement within the tank. Regarding measurement, Botelho et al. (2026) use the ratio of distance traveled to fuel consumed, expressed in kilometers per liter. Shakenov et al. (2026) consider consumption per tonne-kilometer, while D'Agostino et al. (2024) use brake-specific fuel consumption (BSFC) to assess average engine efficiency. These approaches show that energy performance can be analyzed in relation to distance, payload, and engine operation.

Trip duration and the allocation of driving time address vehicle utilization and the distribution of time across operational activities. Lee et al. (2026) present a productivity module that combines time records, working and idle time, cycle time, and the number of cycles. Botelho et al. (2026) calculate trip duration as the difference between start and end times and relate it to distance to determine average speed. This analysis also makes it possible to distinguish activities performed during the working day. Ettousy, Zyane, and Jamiri (2025) identify three main categories: stops, ignition-on time, and active driving. By comparing planned and actual routes, Anghelache et al. (2023) identified reductions of 14.2% in trip duration and 19.6% in average distance traveled. Time and movement records therefore make it possible to monitor operational execution and support decisions on vehicle scheduling and allocation.

Vehicle health, diagnostics, and predictive maintenance are associated with monitoring the mechanical and operational condition of vehicles using variables such as engine temperature, tire pressure, brake use, vibration, and oil pressure. Farahpoor et al. (2024) describe sensors capable of monitoring the engine, transmission, coolant, and braking systems. In predictive maintenance, Viscenheski et al. (2026, p. 3) combine vehicle records and repair information to identify patterns preceding failures. Shakenov et al. (2026) use RMS vibration, suspension stress, and maintenance records to assess mechanical loading risks. Nagy et al. (2021) assess oil condition using parameters such as oxidation, nitration, and soot content. Integrating sensors, maintenance histories, and component parameters therefore enables vehicle reliability monitoring and the identification of potential intervention needs.

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Inactivity and engine idling make it possible to identify periods of non-operation and distinguish productive work from unproductive vehicle use. Lee et al. (2026) classify working and idle time based on movement and stop duration. Priya et al. (2019) complement this analysis by classifying vehicle states according to engine status and changes in location, distinguishing between engine off, vehicle moving, and vehicle stationary with the engine running. The relevance of this monitoring is demonstrated by Ettousy, Zyane, and Jamiri (2025), who identified fuel consumption of 104.80 liters during engine idling, including 24 liters in a single vehicle with no recorded distance traveled. The authors also observed a 23.7% reduction in idling time after combining automation and driver training. These results demonstrate the importance of linking ignition records, location, stop duration, and fuel consumption to identify operational waste.

Route accuracy, tracking, and route compliance concern the monitoring of vehicle movements and the comparison of planned and actual routes. Yu et al. (2026) emphasize that GPS records make it possible to reconstruct trips and trip chains, identifying patterns in vehicle trajectories. Sharma et al. (2026) consider traffic, road conditions, terrain, and distance when assessing vehicle–route suitability. Melkonyan et al. (2026) also use real-time location data, planned and actual routes, and timestamps for trailer coupling and uncoupling. Positioning data therefore enable the assessment of route compliance, the identification of deviations, and the optimization of vehicle movements.

Speed and movement dynamics characterize vehicle motion through variables such as instantaneous speed, average speed, and acceleration. Oliveira et al. (2023) use speed and location records collected every ten seconds to create heatmaps of movement patterns. Shakenov et al. (2026) analyze road segment traversal speed by aligning GPS/VIMS records, while Stancel and Surugiu (2017) use speed to determine averages for monitored segments and generate traffic reports. Abu-Abed and Ivanov (2021) extend this analysis using acceleration and steering angle measurements, highlighting median acceleration as a variable for characterizing movement. Shakenov et al. (2026) also use telematics records collected at 1 Hz to monitor variations in

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speed, vibration, and braking. Combining this information makes it possible to assess traffic conditions and the consistency of vehicle movements.

Driver behavior and driving aggressiveness can be assessed through acceleration and braking events, speed variations, torque, and the use of auxiliary vehicle systems. Szcześniak and Gorzelańczyk (2024) identify the number of braking events as a variable related to driving technique. Aldossary et al. (2026) present the Driving Aggressiveness Index (DAI), comprising rapid acceleration, harsh braking, speeding, and large changes in acceleration (jerk). D'Agostino et al. (2024) use relative positive acceleration (RPA) and relative positive percentage torque variation (RPPTv) to characterize driving dynamics from variations in speed, torque, and accelerator position. Szcześniak and Gorzelańczyk (2024) also identify an association between a one-unit increase in braking cycles and an additional 0.1086 liters of fuel consumption, holding the other variables constant. They further identify the duration of cruise control and retarder use as relevant variables (SZCZEŚNIAK; GORZELAŃCZYK, 2024). Telematics data therefore make it possible to identify driving patterns and analyze their relationships with fuel consumption and fleet operational performance.

The results should be interpreted in light of the limitations of this review. The searches covered four databases, publications in Portuguese and English, and the period from 2017 to the search date of October 17, 2026. Requiring the maximum score on the assessment restricted the sample and may have excluded relevant studies with less information available. In addition, the observed frequencies depend on the category grouping criteria, and the detailed examination of seven categories involved a choice among tied categories. The results therefore describe the literature selected under these criteria, and their application to other fleets requires consideration of the characteristics of each operation.

4. Conclusions

This review aimed to map performance indicators based on telematics data identified in the scientific literature and to understand the information used in their development and analysis in fleet management. A scoping review was conducted and reported following PRISMA-ScR, including 23 studies. The analysis identified 15 indicator categories, seven of which were selected for detailed examination. These

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categories encompass fuel consumption and efficiency, trip duration and allocation of driving time, vehicle health and predictive maintenance, inactivity and engine idling, route compliance, speed and movement dynamics, and driver behavior.

The telematics data, supplementary records, and derived metrics used to analyze these categories were also mapped. The results show that telematics applications cover different aspects of fleet management, from energy efficiency to driver behavior. Fuel consumption and efficiency was the most frequent category, appearing in 43.5% of the studies analyzed, indicating the attention given to energy performance in the selected sample.

The studies present applications in different countries and fleet types, including heavy-duty trucks, commercial vehicles, buses, passenger vehicles, electric vehicles, tractors, and mining equipment. This diversity shows the breadth of vehicle monitoring applications while requiring that the characteristics of each operation be considered when selecting indicators. Measures used in one fleet may require adaptations to adequately represent the performance of another.

The main contribution of this review lies in organizing indicator categories and their relationships with the information used in the studies. By bringing these elements together, the review provides a reference for identifying which operational aspects are monitored and which data are required for their assessment. The synthesis also identifies the use of supplementary records and metrics calculated from information collected by telematics systems.

Certain limitations should be considered. Searches were restricted to four databases, publications in Portuguese and English, and the period from 2017 to October 17, 2026. Prioritizing open-access documents led to the exclusion of 143 of the 211 identified reports—which could not be assessed or included in the synthesis—potentially introducing availability bias. The requirement for a maximum score during the evaluation process also reduced the sample size, and the selection of seven categories involved making choices among categories with equivalent frequencies. Furthermore, differences in the types of outlets, operational contexts, information sources, and measurement methods complicate direct comparisons. Consequently, the findings represent a synthesis of the retrieved and eligible studies rather than an

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exhaustive overview of the topic; the effectiveness of these indicators in improving organizational outcomes remains to be empirically investigated.

Future research can assess the application of the selected categories in actual operations, detailing the specific indicators, their calculation methods, and their use in management processes. Studies examining the relationships between these indicators and costs, energy consumption, productivity, vehicle availability, and safety are also relevant. Joint analysis of these measures may help explain, for example, how driver behavior relates to fuel consumption and how maintenance influences fleet availability.

The findings provide a basis for selecting and studying indicators associated with vehicle telematics. Their use in management depends on how the measures are defined, the quality of the data, and the interpretation of results according to the needs of each operation. Investigating these conditions may improve understanding of how the available information contributes to planning, control, and decision-making in fleet management.

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