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Integrated Data Visualization Dashboard as a Decision Support System in Monitoring Overdimensional and Overload Violations in Indonesia

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ABSTRACT

Purpose: Over Dimension Over Load (ODOL) violations in highway-based freight transportation in Indonesia contribute to infrastructure damage worth Rp43 trillion per year and rank as the second largest cause of national traffic accidents, yet existing monitoring remains partial, fragmented across agencies, and unable to support real-time, data-driven decisions. This study aims to advance understanding of multi-source data integration patterns, analytic design principles, and hierarchical interface architectures that together constitute a conceptual Decision Support System (DSS) framework for comprehensive ODOL surveillance in Indonesia.

Research Design and Methodology: The method used is a Systematic Literature Review following the PRISMA protocol, sourced from Scopus, producing 30 indexed articles meeting inclusion criteria within 2022 to 2026.

Findings and Discussion: The synthesis resulted in an architectural model, the Integrated ODOL Surveillance Dashboard (IOSD), comprising three functional layers: a multi-source data acquisition and integration layer; an analytics layer with violation detection, machine learning-based prediction, spatial analytics, and model interpretability modules; and an interactive visualization layer customized by user role. The model integrates Weigh in Motion, Automatic Number Plate Recognition, AI-based computer vision, and geographic information system data into a single real-time DSS platform spanning field operations to national policy formulation. Comparative insights from international heavy-vehicle monitoring practices further inform the model's institutional design.

Implications: This research contributes a digital, accurate, cross-agency technical framework for ODOL supervision and opens a follow-up agenda for empirical validation of the IOSD prototype under real operational conditions within Indonesia's UPPKB network.

Introduction

Road-based freight transportation remains a critical component of Indonesia's national logistics system. However, its operation continues to be challenged by the persistent use of freight vehicles whose dimensions and/or loads exceed legally permitted limits, commonly referred to as Over Dimension and Over Load (ODOL) vehicles. Rather than representing isolated violations, ODOL practices have evolved into a structural problem involving interactions among logistics costs, operator behaviour, regulatory compliance, infrastructure capacity, and enforcement effectiveness. Recent empirical evidence demonstrates the persistence of this problem. Widyanti et al. (2025), for example, estimated that the prevalence of ODOL trucks on Indonesian highways reached 37.78%, indicating that excessive dimensions and loading remain widespread despite regulatory and enforcement interventions. Their findings further show that perceived severity, perceived barriers, cues to action, and non-legal sanctions significantly influence drivers' intentions to operate ODOL vehicles.

The persistence of ODOL practices has substantial implications for both road safety and infrastructure sustainability. Excessive vehicle loads accelerate pavement deterioration, increase pressure on road and bridge structures, reduce vehicle manoeuvrability, and potentially increase the severity of traffic accidents. According to the Directorate General of Land Transportation, the Indonesian government incurs approximately IDR 43 trillion annually in road and bridge repair costs associated with ODOL operations (Directorate General of Land Transportation [DGLT], 2024a). The scale of non-compliance is also evident in enforcement operations. During an intensive freight-vehicle inspection conducted in August 2024, 8,096 vehicles were inspected, of which 4,345 vehicles (53.66%) were found to have violated applicable requirements. Among these violations, overloading represented the largest category, involving 2,067 vehicles (47.57%) (DGLT, 2024b). These figures demonstrate that ODOL is not merely a technical vehicle-compliance problem but a systemic transportation governance challenge requiring more comprehensive surveillance, data integration, and evidence-based decision support.

Existing regulatory and technological interventions have attempted to strengthen ODOL surveillance through Motor Vehicle Weighing Implementation Units (Unit Pelaksana Penimbangan Kendaraan Bermotor [UPPKB]) and the adoption of Weigh-in-Motion (WIM) technology. WIM represents an important advancement because it enables vehicle weight characteristics to be captured while vehicles are moving, thereby reducing dependence on conventional static weighing processes. Nevertheless, evidence suggests that technological deployment alone does not automatically produce effective enforcement. Rahmatika et al. (2024), evaluating WIM implementation at UPPKB Kulwaru using the PIECES framework, reported an effectiveness score of 77.4%. Although WIM improved vehicle-weighing recording and monitoring, the system remained primarily oriented toward information capture and had not yet developed sufficient electronic enforcement capabilities to directly address ODOL violations. This indicates a critical distinction between data acquisition capability and decision-support capability: a surveillance technology may successfully generate data without necessarily transforming those data into coordinated enforcement decisions.

The limitations of conventional inspection become even more apparent when surveillance capacity is compared with actual freight traffic volumes. Evidence from UPPKB Pallangga in Gowa Regency demonstrates the magnitude of this problem. Asrib et al. (2026) analysed 638 freight vehicles and found that significant ODOL violations accounted for 19.75% of inspected vehicles, with extreme overloading reaching up to 139.75% above the permitted load threshold. More importantly, the UPPKB was able to inspect only approximately 2.39% of the estimated 3,814 freight vehicles passing the corridor each day, implying a surveillance gap of approximately 97%. Similar evidence from UPPKB Tana Batue also indicates persistent weight non-compliance among freight vehicles and highlights the need for stronger enforcement mechanisms and technological support (Hasrul et al., 2025). Consequently, relying exclusively on selective static inspections is unlikely to provide comprehensive coverage of freight movements across major logistics corridors.

These limitations become increasingly important as transportation systems generate larger volumes of heterogeneous data. Contemporary Intelligent Transportation Systems (ITS) can incorporate information from WIM sensors, Automatic Number Plate Recognition (ANPR), traffic cameras, Global Positioning System (GPS) devices, geographic information systems (GIS), and other connected transportation infrastructures. However, the availability of such data does not necessarily guarantee their effective utilisation. Jiang and Luo (2021) emphasise that transportation big data originate from heterogeneous sources and require appropriate integration and analytical mechanisms before they can effectively support traffic estimation, prediction, and operational decision-making. Similarly, Huynh et al. (2024) argue that ITS-enabled freight transportation increasingly depends on the ability to integrate datasets characterised by different formats, spatial resolutions, temporal scales, and analytical requirements.

This challenge is particularly relevant to freight transportation visualisation. Ma et al. (2022) demonstrate that although substantial investments have been made in collecting freight movement and location-based telematics data, much of the resulting information remains underutilised for operational and strategic decision-making. Their review proposes a taxonomy linking data abstraction, analytical objectives, and visualisation techniques and emphasises the importance of decision-support mechanisms that enable analysts and policymakers to select and interpret appropriate freight visualisations. The literature therefore suggests that the central challenge has shifted from merely collecting transportation data toward converting heterogeneous and high-volume data into interpretable, actionable, and role-specific information.

Recent advances in artificial intelligence further strengthen the potential for data-driven ODOL surveillance. Deep-learning approaches, for example, have demonstrated the capability to identify overloaded vehicles from structural monitoring and traffic-related data without relying exclusively on conventional static weighing. Li et al. (2023) showed that deep-learning-based overloaded-vehicle identification can extract spatial and temporal features from monitoring data and provide an end-to-end approach to overloaded-vehicle detection under complex traffic conditions. These developments suggest that future ODOL surveillance systems should move beyond descriptive monitoring toward predictive and intelligent surveillance, in which historical violations, vehicle characteristics, spatial patterns, temporal behaviour, and real-time sensor observations can collectively support risk prediction and enforcement prioritisation.

Research Gap

Despite these technological developments, the existing literature remains fragmented across several research streams. Studies conducted in Indonesia have predominantly examined vehicle compliance and ODOL prevalence (Asrib et al., 2026; Hasrul et al., 2025; Widyanti et al., 2025), WIM effectiveness (Rahmatika et al., 2024), and regulatory or enforcement mechanisms. International transportation studies, meanwhile, have focused extensively on big-data analytics, freight visualisation, ITS, predictive traffic modelling, and overloaded-vehicle identification (Huynh et al., 2024; Jiang & Luo, 2021; Li et al., 2023; Ma et al., 2022).

However, limited attention has been given to integrating these technological and analytical components into a unified Decision Support System (DSS) specifically designed for ODOL surveillance. In particular, the literature has not sufficiently addressed how heterogeneous ODOL-related data—including UPPKB weighing records, WIM measurements, ANPR data, computer-vision outputs, vehicle identification records, spatial information, and historical violation patterns—can be systematically integrated, analysed, and visualised within a single decision-oriented architecture. The gap is therefore not simply the absence of surveillance data or individual detection technologies; rather, it lies in the absence of an integrated analytical architecture capable of transforming fragmented ODOL surveillance data into real-time, interpretable, predictive, and role-specific decision intelligence.

This distinction is important because existing ODOL surveillance largely addresses detection, whereas effective transportation governance requires a broader decision cycle encompassing detection, integration, interpretation, prediction, prioritisation, visualisation, and enforcement support. Accordingly, the scientific challenge is to determine how these components can be structured within a coherent architecture that supports decision-making at operational, analytical, and policy levels.

Research Novelty

Against this background, the novelty of this study lies in proposing an Integrated ODOL Surveillance Dashboard (IOSD) as a data-driven Decision Support System that conceptually integrates heterogeneous surveillance technologies and analytical mechanisms within a unified architecture. Rather than treating WIM, ANPR, computer vision, GIS, historical violation records, and freight-vehicle databases as independent technological instruments, the proposed IOSD model conceptualises them as interconnected components of an integrated surveillance ecosystem.

The proposed model advances previous research in four principal dimensions. First, at the data layer, it integrates heterogeneous surveillance sources, including UPPKB records, WIM measurements, ANPR observations, computer-vision outputs, and spatial-temporal violation histories. Second, at the analytics layer, it combines rule-based violation detection with predictive analytics, spatial analysis, and interpretable machine-learning mechanisms. Third, at the visualisation layer, it translates multidimensional ODOL information into interactive and decision-oriented visual representations. Fourth, at the decision layer, it introduces a role-based information hierarchy that differentiates the operational requirements of field enforcement officers, analytical requirements of transportation analysts, and strategic requirements of policymakers.

Accordingly, the conceptual contribution of this study extends beyond the development of another transportation dashboard. It proposes a transition from fragmented surveillance toward integrated decision intelligence, thereby positioning data integration, analytics, visualisation, and stakeholder-specific decision support as interconnected components of ODOL governance.

Research Questions

Based on the identified research gap, this study addresses the overarching question of how an integrated data-visualisation architecture can be designed to function effectively as a Decision Support System for ODOL surveillance in Indonesia. This overarching problem is operationalised through five hierarchically structured research questions:

RQ1 – Data Foundation: What types, sources, characteristics, and interoperability patterns of surveillance data are critical for enabling comprehensive and near-real-time ODOL detection within the Indonesian road-freight transportation system?

RQ2 – Integration Architecture: What data-integration architecture and interoperability mechanisms are required to consolidate heterogeneous data from UPPKB systems, WIM, ANPR, AI-based computer vision, GIS, and historical violation databases into a unified DSS environment?

RQ3 – Analytical Intelligence: What analytical and predictive mechanisms—including rule-based violation detection, machine-learning prediction, spatial analytics, and model interpretability—are required to support both reactive enforcement and proactive ODOL-risk prevention?

RQ4 – Visualisation Design: What data-visualisation patterns most effectively transform multidimensional ODOL surveillance outputs into interpretable and actionable information for different transportation stakeholders?

RQ5 – Decision and Interface Hierarchy: How should an integrated ODOL surveillance dashboard structure its information and interface hierarchy to accommodate the differentiated decision-making needs of field officers, transportation analysts, and policymakers?

Together, these questions establish a sequential analytical framework progressing from data identification and interoperability (RQ1), system integration (RQ2), analytical intelligence (RQ3), information visualisation (RQ4), to stakeholder-oriented decision support (RQ5). The synthesis of these five dimensions forms the conceptual foundation for the proposed Integrated ODOL Surveillance Dashboard (IOSD) architectural model.

Figure 1. Mind Map of Research Questions Guiding the Design of the Integrated ODOL Surveillance Dashboard (IOSD)

The scientific contribution of this research lies in synthesizing three interrelated dimensions: identifying critical data source and interoperability patterns, formulating analytic design principles for multi-source data processing and visualization, and constructing the Integrated ODOL Surveillance Dashboard (IOSD), a conceptual DSS framework operationalized into a coherent three-layer architecture comprising data acquisition, analytics, and visualization. Theoretically, this research contributes a synthesized conceptual model for future empirical validation and prototype development. Practically, the findings are expected to inform the Ministry of Transportation, the National Police Corps, and the Ministry of Public Works in building a more integrated, transparent, cross-agency ODOL surveillance ecosystem, ultimately contributing to reduced accident rates, extended road infrastructure lifespan, and more efficient allocation of national road maintenance budgets.

Literature Review

The conceptual and technological foundation of this study is situated at the intersection of three interconnected research domains: **sensor-based vehicle weighing and data reliability, artificial-intelligence-assisted traffic surveillance and geospatial analytics, and dashboard-based decision support systems (DSS)**. Recent transportation research increasingly demonstrates that effective monitoring systems depend not merely on the availability of individual technologies but on their capacity to generate reliable data, integrate heterogeneous information sources, support advanced analytics, and communicate actionable information to different decision-makers (Jiang & Luo, 2022; Ma et al., 2022). Accordingly, the literature is synthesised thematically to identify the technological capabilities, limitations, and integration requirements that provide the conceptual foundation for the proposed **Integrated ODOL Surveillance Dashboard (IOSD)**.

Reliability and Data Continuity in Weigh-in-Motion Systems

Accurate and continuous vehicle-load measurement constitutes the fundamental data layer of an effective overload surveillance system. **Weigh-in-Motion (WIM)** technologies have consequently received considerable attention because they enable axle loads and gross vehicle weights to be estimated while vehicles remain in motion, thereby supporting substantially higher monitoring coverage than conventional static weighing procedures. Recent developments in WIM technology demonstrate increasing potential for continuous traffic-load monitoring, infrastructure assessment, and automated freight-vehicle screening (Burnos & Rys, 2017; Lydon et al., 2016).

Nevertheless, the operational value of WIM depends heavily on measurement accuracy, calibration stability, environmental sensitivity, and long-term sensor reliability. Burnos and Rys (2017) demonstrated that WIM accuracy is influenced not only by sensor characteristics but also by pavement conditions, vehicle dynamics, temperature, and other environmental factors. These findings are particularly important for real-time surveillance systems because inaccurate or unstable measurements can propagate through subsequent analytical processes and ultimately generate unreliable enforcement decisions. Consequently, WIM data should not be treated merely as raw measurements but as information accompanied by indicators of calibration status, measurement confidence, sensor condition, and temporal validity.

Long-term sensor reliability is equally important because an integrated surveillance dashboard requires continuous rather than episodic data availability. Failures involving strain gauges, piezoelectric sensors, communication networks, or data-acquisition components can create missing observations and consequently compromise the temporal continuity of monitoring. Within Bridge Weigh-in-Motion (BWIM) environments, advances in signal processing and data-driven approaches have increasingly enabled traffic loads and vehicle characteristics to be reconstructed from structural-response data (Sekiya et al., 2018). Such approaches illustrate the potential for intelligent fault handling and data reconstruction when direct measurements become incomplete.

From a DSS perspective, however, reconstructed or estimated observations should not be treated identically to directly measured values. The distinction between **measured, estimated, reconstructed, and potentially unreliable data** becomes essential for transparency and decision accountability. A field officer deciding whether a vehicle should be subjected to further inspection requires a different degree of evidential certainty from an analyst examining aggregate traffic patterns. Accordingly, sensor reliability must be represented not only within the data-processing layer but also within the visualisation layer through confidence indicators, sensor-health information, anomaly flags, or differentiated data-quality markers.

This observation reveals an important limitation in the existing WIM literature. Although considerable attention has been devoted to measurement accuracy, calibration, sensor configurations, and infrastructure applications, comparatively limited attention has been given to how **sensor reliability and data-quality uncertainty should be communicated within integrated decision-support interfaces**. The proposed IOSD addresses this issue by treating data quality as an explicit component of surveillance intelligence rather than as a purely technical concern at the sensor level.

Artificial Intelligence, Computer Vision, and Geospatial Intelligence

The second technological domain concerns the increasing application of **artificial intelligence (AI), computer vision, Automatic Number Plate Recognition (ANPR), and Geographic Information Systems (GIS)** to transportation surveillance. These technologies have expanded the capacity of transportation agencies to monitor vehicle identities, trajectories, traffic conditions, and behavioural anomalies beyond the spatial limitations of conventional inspection stations.

Computer-vision-based traffic monitoring has progressed substantially through advances in deep learning and object-detection algorithms. Modern detection architectures can identify, classify, and track vehicles from roadside cameras and video streams with increasingly high computational efficiency (Bochkovskiy et al., 2020). When combined with ANPR, such systems can associate observed vehicle movements with registration identifiers, enabling historical movement records and repeated violation patterns to be analysed across multiple locations.

For ODOL surveillance, this capability is strategically important. Conventional WIM or UPPKB systems primarily determine whether a vehicle violates dimensional or weight requirements at a particular inspection location. In contrast, ANPR and computer vision can potentially extend surveillance across a broader road network by tracking the same vehicle across different spatial and temporal contexts. This enables the analytical focus to shift from isolated violations toward **vehicle-level violation histories, recurring routes, temporal patterns, and risk profiles**.

GIS provides an additional analytical dimension by transforming individual observations into spatial intelligence. Transportation big-data research demonstrates that integrating heterogeneous sensor, trajectory, GPS, camera, and infrastructure datasets enables traffic patterns to be analysed at multiple spatial and temporal scales (Jiang & Luo, 2022). In an ODOL context, GIS-based analysis could therefore support the identification of violation hotspots, frequently used ODOL corridors, temporal clusters, high-risk logistics routes, and spatial relationships between weighing stations and observed freight movements.

However, AI- and GIS-based surveillance also presents an important methodological limitation. Image recognition and vehicle tracking can identify vehicle categories, licence plates, movement patterns, and potentially abnormal dimensional characteristics, but they do not necessarily provide legally sufficient evidence of vehicle weight. Consequently, AI-based surveillance should not be conceptualised as a substitute for WIM or certified weighing infrastructure.

Instead, the technologies are functionally complementary. **WIM provides load evidence; ANPR establishes vehicle identity; computer vision provides visual and dimensional intelligence; and GIS establishes spatial-temporal context.** Integrating these functions creates a considerably richer surveillance environment than deploying any single technology independently.

This complementarity provides a central rationale for the IOSD architecture. Rather than asking which technology should replace conventional ODOL surveillance, this study asks how heterogeneous surveillance technologies can be orchestrated within a unified DSS so that the strengths of one data source compensate for the limitations of another.

Transportation Big Data and Multi-Source Data Integration

The increasing availability of transportation sensors has created another challenge: **data abundance does not automatically generate decision intelligence**. Contemporary transportation environments produce large volumes of heterogeneous information characterised by different formats, sampling frequencies, spatial resolutions, levels of accuracy, and institutional ownership.

Jiang and Luo (2022) emphasise that traffic estimation and prediction increasingly depend on the ability to integrate heterogeneous data generated by fixed sensors, mobile devices, GPS trajectories, cameras, and connected transportation infrastructure. However, combining these datasets requires mechanisms for data cleaning, temporal synchronisation, spatial alignment, interoperability, and analytical transformation.

These challenges are particularly relevant to ODOL surveillance in Indonesia because the relevant data potentially originate from multiple technological and institutional systems. UPPKB databases contain weighing and inspection records; WIM systems generate continuous vehicle-load observations; ANPR cameras produce vehicle-identity data; computer-vision systems generate image-derived classifications; GIS provides spatial information; and vehicle-registration databases contain administrative characteristics.

Consequently, the core technical problem is no longer simply **data collection**, but **data interoperability**.

An integrated ODOL surveillance architecture must therefore establish mechanisms through which these heterogeneous observations can be associated with common entities, particularly individual vehicles, locations, and timestamps. Without such integration, surveillance remains fragmented: agencies may possess substantial volumes of data while lacking the ability to generate a coherent representation of vehicle behaviour across the transportation network.

Data Visualization and Decision-Support Dashboard Design

The third major research domain concerns the transformation of integrated transportation data into interpretable and actionable information. Data visualisation is particularly important in complex transportation systems because decision-makers must interpret multidimensional information under different temporal and operational constraints.

Ma et al. (2022), in their review of freight transportation data visualisation, demonstrate that although extensive freight-movement and telematics data are increasingly available, these datasets remain underutilised for operational and strategic decision-making. Their study proposes a taxonomy connecting freight-data characteristics, analytical objectives, and visualisation approaches, demonstrating that effective visualisation should be determined by the decision problem rather than merely by the available dataset.

This principle has important implications for ODOL surveillance. A dashboard containing large quantities of information does not necessarily constitute an effective DSS. Its effectiveness depends on whether the interface enables users to identify violations, interpret patterns, prioritise interventions, and understand uncertainty rapidly.

Accordingly, visualisation requirements differ across stakeholder groups. **Field enforcement officers** require immediate operational information such as vehicle identity, current load status, violation severity, and recommended inspection actions. **Transportation analysts** require historical trends, spatial distributions, correlations, recurring vehicle patterns, and predictive indicators. **Policymakers**, meanwhile, require aggregated indicators concerning compliance rates, high-risk corridors, enforcement performance, infrastructure implications, and policy outcomes.

This differentiation is consistent with contemporary dashboard research emphasising that effective interfaces must align information complexity with user roles and decision tasks. User-centred dashboard development therefore requires more than graphical attractiveness; it requires appropriate information hierarchy, interaction mechanisms, visual encoding, contextual information, and cognitive efficiency.

For an ODOL DSS, the challenge is consequently to transform the same underlying surveillance ecosystem into **different levels of decision intelligence according to stakeholder responsibility**.

Decision Support Systems and Integrated Surveillance Architecture

A DSS extends beyond conventional monitoring because its purpose is not simply to display what has occurred but to support decisions regarding **what requires attention, why it matters, and what action should follow**. Contemporary smart-city and intelligent-transportation architectures increasingly integrate real-time sensing, analytical engines, geospatial information, and visual interfaces to support operational decision-making.

Transportation big-data systems similarly demonstrate an evolution from descriptive monitoring toward predictive and prescriptive intelligence. Machine-learning techniques can identify patterns from historical transportation observations and support traffic prediction, anomaly detection, classification, and risk estimation (Jiang & Luo, 2022). For overloaded-vehicle monitoring specifically, recent research has demonstrated the feasibility of deep-learning approaches for identifying overloaded vehicles using spatial-temporal traffic and structural monitoring information (Li et al., 2023).

These developments create opportunities for ODOL surveillance to progress through several analytical stages:

descriptive monitoring → violation detection → diagnostic analysis → predictive risk assessment → enforcement prioritisation.

Such progression is particularly important in Indonesia because inspection resources are inherently limited. A DSS capable of estimating which vehicles, corridors, operators, or time periods exhibit the highest ODOL risk could enable enforcement agencies to allocate inspection resources more strategically rather than relying exclusively on random or static inspection.

However, predictive functionality introduces an additional requirement: **interpretability**. Enforcement decisions have regulatory and potentially legal consequences. Therefore, predictions generated by machine-learning models should not function as unexplained algorithmic outputs. Decision-makers need to understand the factors contributing to a vehicle's risk classification. Model interpretability and uncertainty communication should consequently be incorporated into the analytical and interface layers of an ODOL DSS.

Synthesis and Identified Research Gap

Taken collectively, the literature demonstrates substantial advances within individual technological domains. WIM research has improved the accuracy and continuity of vehicle-load measurement (Burnos & Rys, 2017); computer vision and AI have expanded automated vehicle detection capabilities (Bochkovskiy et al., 2020); transportation big-data research has developed increasingly sophisticated approaches to heterogeneous data integration and prediction (Jiang & Luo, 2022); freight visualisation research has established the importance of aligning visual representations with analytical objectives (Ma et al., 2022); and recent machine-learning applications demonstrate the potential for intelligent overloaded-vehicle identification (Li et al., 2023).

Nevertheless, these research streams remain predominantly **technologically fragmented**. Existing studies typically optimise one component of the surveillance process—measurement, detection, prediction, geospatial analysis, or visualisation—without systematically integrating these capabilities into a single ODOL-specific decision-support architecture.

More specifically, three interrelated gaps remain. First, a **data-integration gap** exists concerning how heterogeneous WIM, ANPR, computer-vision, GIS, vehicle-registration, and historical violation data can be synchronised within a common surveillance environment. Second, an **analytical gap** concerns how descriptive monitoring can be combined with predictive risk assessment and interpretable analytics to support proactive enforcement. Third, an **interface and governance gap** concerns how integrated surveillance intelligence should be differentiated according to the operational, analytical, and strategic requirements of multiple stakeholders.

The present study addresses these interconnected gaps through the proposed **Integrated ODOL Surveillance Dashboard (IOSD)**. Conceptually, the IOSD links five sequential layers—**data acquisition, data integration, analytical intelligence, interactive visualisation, and role-based decision support**—thereby shifting ODOL surveillance from isolated technological monitoring toward an integrated decision-intelligence architecture.

Research Design and Methodology

This study employed a **Systematic Literature Review (SLR)** approach guided by the **Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020** framework. The SLR approach was selected to enable a systematic, transparent, and reproducible process for identifying, screening, evaluating, and synthesising relevant previous studies. PRISMA 2020 provides structured reporting guidance for systematic reviews by requiring researchers to clearly document how records are identified, excluded, retrieved, assessed for eligibility, and ultimately included in the final synthesis (Page et al., 2021). This framework improves methodological transparency and allows readers to evaluate the completeness and traceability of the literature-selection process.

The review was specifically designed to examine the scholarly literature concerning **data visualisation dashboards, Decision Support Systems (DSS), Over Dimension and Over Load (ODOL) surveillance, freight transportation monitoring, and multi-source transportation data integration**. The methodological process comprised the formulation of the review scope and eligibility criteria, identification of information sources, development of the search strategy, screening and eligibility assessment, data extraction, and thematic synthesis. These procedures are consistent with contemporary systematic-review practices that emphasise explicit research questions, reproducible search strategies, predetermined eligibility criteria, and transparent study-selection procedures (Page et al., 2021; Rethlefsen et al., 2022).

Information Source and Search Strategy

The literature search was conducted using the **Scopus database** as the principal bibliographic source. Scopus was selected because it provides multidisciplinary coverage of peer-reviewed academic literature and offers structured search functions that facilitate systematic retrieval using combinations of keywords, Boolean operators, publication periods, document types, and subject areas. Comparative studies of academic databases have also identified Scopus as one of the principal multidisciplinary sources used for structured scholarly searches and bibliometric research, although differences in coverage across databases should be acknowledged (Gusenbauer & Haddaway, 2020; Pranckutė, 2021).

The search strategy combined terms representing the principal technological and conceptual dimensions of the study. The keywords included **“dashboard visualization,” “decision support system,” “overload,” “over dimension overload,” “freight transportation,” “weigh-in-motion,” “traffic surveillance,” “data integration,” “artificial intelligence,” “ANPR,”** and **“geographic information system.”** Boolean operators such as **AND** and **OR** were applied to broaden or narrow the search according to the relationships among these concepts. Search terms were applied to relevant Scopus fields, particularly article titles, abstracts, and keywords, to increase the likelihood of retrieving studies directly related to the research questions.

The review focused on publications from **2022 to 2026** to capture recent technological developments in transportation surveillance, artificial intelligence, data integration, and dashboard-based decision support. Only peer-reviewed studies with accessible full-text content and direct conceptual or technological relevance to the proposed Integrated ODOL Surveillance Dashboard (IOSD) were considered for inclusion.

Eligibility Criteria

Studies were included when they satisfied several predetermined criteria. Eligible publications had to be published between **2022 and 2026**, indexed in Scopus, available in full text, and directly related to at least one of the principal domains of the review: transportation data visualisation, Decision Support Systems, ODOL or overloaded-vehicle surveillance, WIM technology, AI-assisted traffic monitoring, GIS-based transportation analysis, or transportation-data integration.

Studies were excluded when they did not address transportation or surveillance applications relevant to the research objectives, provided insufficient discussion of data visualisation or decision-support functionality, lacked accessible full-text content, fell outside the specified publication period, or represented duplicate or retracted records. Establishing inclusion and exclusion criteria before the final synthesis is important for reducing arbitrary study selection and improving methodological reproducibility in systematic reviews (Page et al., 2021).

PRISMA-Based Study Selection

The study-selection procedure was documented using the **PRISMA 2020 flow diagram**, which provides a transparent representation of the number of records identified, screened, retrieved, excluded, and included in a systematic review (Page et al., 2021).

The initial Scopus search identified **309 records**. During the identification process, **102 duplicate or retracted records were removed**, resulting in **207 records** entering title and abstract screening. At this stage, **95 records were excluded** because their topics were not sufficiently relevant to the objectives of the review. Consequently, **112 reports were sought for full-text retrieval**.

Of these 112 reports, **56 could not be retrieved in full text**, leaving **56 reports for full-text eligibility assessment**. The distinction between records identified during database searching, records screened by title and abstract, reports sought for retrieval, and reports assessed for eligibility follows the reporting terminology recommended in PRISMA 2020 (Page et al., 2021; Rethlefsen et al., 2022).

The remaining 56 full-text studies were evaluated against the predetermined eligibility criteria concerning topical relevance, publication period, full-text availability, and their contribution to the technological or conceptual dimensions of ODOL surveillance. During this assessment, **26 studies were excluded**. Of these, **17 studies were excluded because they did not provide sufficiently specific contributions to data visualisation or dashboard design**, while **nine studies were excluded because their technological or analytical contexts were not sufficiently relevant to transportation surveillance and ODOL-related decision support**.

Following this process, **30 studies satisfied all eligibility criteria and were included in the final qualitative synthesis**. The progressive reduction from the initial search results to the final study set was systematically documented to maintain traceability and minimise ambiguity regarding the basis for study inclusion and exclusion.

Data Extraction and Thematic Synthesis

The 30 included studies were subsequently analysed using a **thematic synthesis approach**. Rather than merely summarising each publication individually, the analysis focused on identifying recurring technological capabilities, methodological approaches, architectural characteristics, limitations, and research gaps across the selected studies. Thematic synthesis is particularly useful for systematically organising findings across heterogeneous studies and developing higher-level interpretive themes from recurring patterns in the literature (McMahon et al., 2022).

The synthesis generated several interconnected thematic clusters, including **WIM and mobile vehicle-weighing technologies, sensor reliability and data continuity, AI- and computer-vision-based traffic surveillance, ANPR-enabled vehicle identification, GIS and spatial analytics,**

transportation data visualisation, heterogeneous data integration, predictive analytics, and DSS architecture. These themes were subsequently compared across studies to identify technological complementarities, recurring limitations, and areas in which existing research remained fragmented.

Particular attention was given to how individual technologies contributed to different stages of the ODOL surveillance process. For example, WIM-related studies were examined primarily in terms of vehicle-load measurement and sensor reliability; AI and computer-vision studies were evaluated in relation to automated vehicle detection and classification; GIS-oriented studies were analysed in terms of spatial and temporal pattern identification; and dashboard and DSS studies were examined according to their ability to transform heterogeneous data into interpretable and actionable information.

The final stage involved **cross-study synthesis**, in which relationships among the thematic clusters were mapped onto the proposed IOSD architecture. Evidence concerning data acquisition informed the system's **data-source layer**; studies concerning interoperability and heterogeneous datasets informed the **data-integration layer**; research on AI, prediction, and spatial analytics informed the **analytical-intelligence layer**; dashboard and visualisation research informed the **visualisation layer**; and DSS-related studies informed the **role-based decision-support layer**.

Through this procedure, the IOSD model was not derived from a single technological study or predetermined system configuration. Instead, each architectural component was developed from recurring findings, identified limitations, and technological relationships emerging from the systematic synthesis of the selected literature. The entire review process was documented to maintain traceability between the included evidence, identified thematic findings, research questions, and each component of the proposed **Integrated ODOL Surveillance Dashboard (IOSD)**.

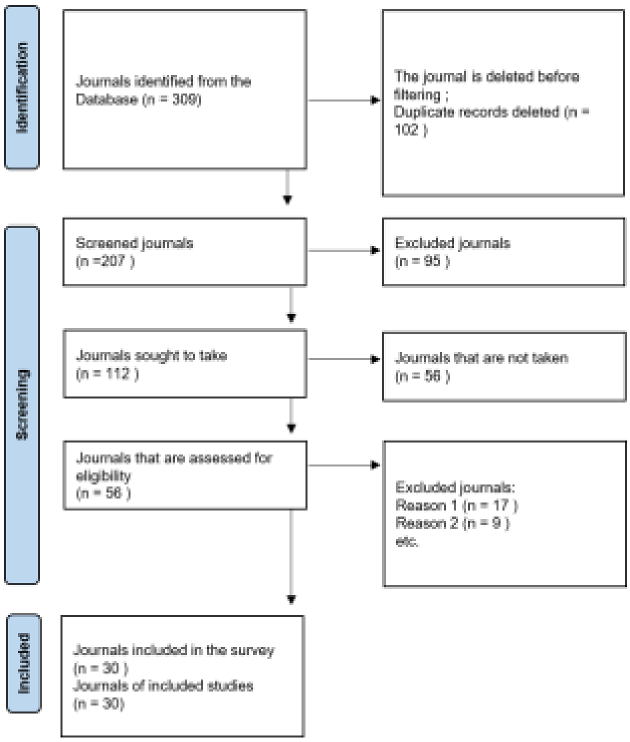

Figure 2. Flowchart PRISMA

Findings and Discussion

Findings

A total of 30 articles met the inclusion criteria, sourced from Scopus-indexed journals published between 2022 and 2026, substantially addressing integrated data visualization dashboards, Weigh in Motion (WIM) systems, technology-based traffic monitoring, and decision support systems in urban transportation, though few specifically target ODOL surveillance in Indonesia [21]. The additional

fifteen articles strengthen the evidentiary base on WIM sensor accuracy, vision-based overweight detection, and comparative monitoring practices from Saudi Arabia, India, China, and Brazil.
The thirty articles cluster into several thematic groups: WIM-based overload detection [12], [22], [23], [24], [25], sensor- and AI-based traffic monitoring [13], [26], [27], transportation data visualization design [14], [28], [29], [30]. and DSS-related topics, including smart city security [15], congestion prediction (Munadi et al., 2026), and causal graph-based congestion pattern representations [31] A summary of the thirty articles is presented in Table I.

Table 1. Summary of Literature Selection Articles

No	Author and Year	Title	Focus and Key Findings	Research Context	Gap / Limitation
1	Baltzer et al. (2024)	Visualizing the Influence of New Public Transport Infrastructure on Travel Times	Bivariate choropleth map visualization comparing infrastructure impact on travel time	Public transport cartography, Europe	No multi-source integration; limited to one variable pair
2	Delfini et al. (2024)	Visual Analytics for Sustainable Mobility	Interactive map-based dashboard (UrbanFlow Milano) for MaaS data exploration	Urban mobility/MaaS, Italy	No heavy vehicle data; usability not tested with policymakers
3	Deng et al. (2025)	Visual Comparative Analytics of Multimodal Transportation	TraDyssey system with parallel coordinate plots for mode comparison	Large-scale travel analytics	Not tested for freight load monitoring
4	Feng et al. (2024)	TrafPS: Shapley-Based Visual Analytics	Shapley-value interpretability for deep learning traffic prediction	AI traffic prediction interpretability	Not adapted for overload violation prediction
5	Gajda et al. (2025)	Long-Term Assessment of WIM Load Sensor Properties	3-year WIM sensor stability study; 8-month re-verification recommended	WIM performance, Europe	No DSS/dashboard integration
6	González-Villa et al. (2024)	DSS for Safety and Security in Smart Cities	Integrated DSS with real-time evacuation, traffic, risk data	Smart city public safety, Europe	Not tested in cross-agency interoperability contexts like Indonesia
7	Jiang et al. (2025)	Real-Time Urban Traffic Monitoring via Transit Buses as Probes	GTFS probe-vehicle data, high correlation with reference data	Urban traffic monitoring, Asia	No vehicle identity/load detection
8	Munadi et al. (2026)	Ensemble ML for Traffic Congestion and Travel Time Prediction	GPS IoT-based BRT congestion prediction, low-cost hardware	Urban BRT, Indonesia	No load violation prediction
9	Nguyen et al. (2024)	Interpretable Causal Graph-Based Congestion Patterns	Causal graph framework for congestion pattern retrieval	Large-scale road network analysis	Not tested with WIM/ANPR data
10	Obaidat & Alomari (2026)	Real-Time Multi-Source AI, CV, and GIS Fusion	Computer vision + smartphone sensors + GIS, high-accuracy density mapping	Urban traffic, limited infrastructure	No individual vehicle load verification
11	Ravichandran et al. (2024)	Site-Specific Traffic Modelling Based on WIM	Probabilistic load distribution model from 2 toll-road WIM systems	Structural risk assessment, Italy	No DSS/visualization integration
12	Ryguła et al. (2024)	Stability and Variability in WIM Sensor Readings	3-year stability analysis, no recalibration needed	WIM evaluation, Central Europe	No multi-source integration aspect
13	Szinyéri & Kovari (2026)	Handling Data Loss in BWIM via Time-Series Regression	Regression-based signal reconstruction for sensor failure	BWIM data integrity, Europe	Single-sensor reconstruction only
14	Tsouros et al. (2024)	From Raw Data to Informed Decisions: Online Data Repository + Dashboard	Repository + dashboard for large-scale transport data	Transport data management, Qatar	No freight surveillance or cross-agency design
15	Zhao et al. (2022)	Methodological Study on Truck Driving State Influence on WIM Accuracy	YOLOv3 + Deep Residual Network for driving-state correction	WIM accuracy via camera, general	Limited to per-vehicle correction, no dashboard aggregation

16	Alobaidallah et al. (2025)	Safety Effectiveness of Automated Traffic Enforcement Systems (ATES)	SLR (PRISMA 2020) on ATES (speed/red-light cameras, mobile units) effectiveness	Road safety enforcement, Saudi Arabia	Public perception and equity of enforcement not fully resolved
17	Gajda et al. (2023)	Accuracy Maps of WIM Systems for Direct Enforcement	Accuracy-map concept to minimize false-positive overload classification	WIM-based legal enforcement, Europe	Sensitive to interfering field factors
18	Callefi et al. (2026)	Roadmap for Prioritising Technology-Enabled Capabilities in Road Freight Transport	12 ICT capabilities identified/validated via mixed-method + fuzzy DEMATEL	ICT adoption roadmap, freight sector	Roadmap not yet tested in cross-agency government context
19	Gao et al. (2023)	Intelligent Traffic Safety Cloud Supervision Based on IoV	Cloud supervision system unifying heterogeneous data via IoV	Urban rail/traffic cloud supervision	Conceptual; limited real-world deployment evidence
20	Hagmanns et al. (2024)	Enhancing WIM Accuracy via Camera-Captured Wheel Oscillations	Fuses WIM data with camera-captured oscillation for correction	WIM accuracy improvement	Limited gain for small oscillation amplitudes
21	Callefi et al. (2025)	Exploring Barriers to ICT Adoption in Road Freight Operations	5 key barriers identified (top management support is most significant)	ICT adoption barriers, Brazil	Barriers not yet linked to a technical DSS architecture
22	Jung & Lee (2024)	Optimal WIM Planning for Multiple Stakeholders	Game-theory model of WIM placement balancing govt/agency/driver costs	WIM network planning	Conceptual model, not field-validated
23	Jung et al. (2025)	WIM Placement for Overloaded Truck Enforcement	Bi-level optimization for WIM location vs. traffic disruption/detour	WIM placement strategy	Simulation-based, needs real network validation
24	Adigopula & Kumar (2025)	Effect of Overloaded Vehicles on Asphalt Pavement (India)	Truck factor analysis across vehicle classes and pavement thickness	Pavement damage, India	Focused on pavement engineering, not surveillance systems
25	Lam et al. (2025)	Vision-Based WIM (V-WIM) for Load Tracking and Identification	YOLOv8 + ByteTrack for weight estimation without embedded sensors	Vision-based WIM	Validated only via limited on-site test
26	Li et al. (2024)	Non-Contact Identification of Overweight Vehicles via CV and Deep Learning	Deep learning + vehicle vibration model for overweight ID	Non-contact overweight detection	Tested on illustrative two-axle vehicle only
27	Liu et al. (2024)	Deep-Learning Detection/Classification of Heavy-Duty Trucks in Satellite Images	CenterNet + Mask R-CNN + GIS for wide-area truck detection	Satellite/GIS truck monitoring, USA	No individual load/plate data
28	Miftahulkhair et al. (2024)	Impact of Losses on Flexible Pavement Due to Vehicle Overloading	Truck factor up to 83% increase; asphalt overlay mitigation	Pavement damage, Indonesia	Engineering-focused, no DSS/dashboard link
29	Wen et al. (2022)	Injury Severity of Overloaded-Truck Crashes on Mountainous Highways	Random parameter logit model, 1,862 crashes analyzed	Crash severity analysis, China	Crash-focused, not real-time surveillance
30	Yang et al. (2023)	Piezoelectric Ceramic WIM Sensor with Temperature Correction	Low-cost PZT-5H sensor with temperature compensation	WIM sensor development	Lab-tested; field-scale deployment not yet evaluated

Based on Table I, it can be identified that the fifteen literature collectively provide a conceptual and technical basis that is relevant to the three main elements in the formulation of this research problem, namely vehicle surveillance data sources (in particular WIM technology and sensor-based or artificial intelligence-based traffic monitoring), data visualization techniques to support the interpretation of information by decision makers, and decision support system architectures that integrate multiple data sources in *real-time*. These three elements then become the analytical framework in the discussion section, which will elaborate in more depth how the findings from the literature can be adapted and synthesized into the design of an *integrated data visualization* dashboard model as a *Decision Support System* in the supervision of ODOL violations in Indonesia.

Discussion

Multi-Source Data Integration Patterns for Real-Time ODOL Surveillance

Designing the IOSD dashboard depends fundamentally on the availability and quality of underlying data sources. Weigh in Motion (WIM) technology, a dynamic weighing system enabling vehicle load measurement without stopping traffic flow, is among the most relevant primary sources. A long-term study of two WIM systems with different sensor technologies found accuracy maintained without recalibration over three years, recommending verification every eight months [22], while a separate analysis of WIM stations confirmed high measurement stability despite dynamic field conditions such as temperature and traffic density changes [23]. These findings confirm that WIM data reliability is a prerequisite for accurate dashboard visualization.

Data loss due to sensor failure, particularly in Bridge Weigh in Motion (BWIM) systems using strain gauges, is another concern. A regression-based time-series reconstruction algorithm has been shown to reduce load-estimation error following sensor failure, in line with the COST 323 standard [12]. , implying that IOSD's backend requires a mechanism for handling missing or incomplete data to keep visualizations reliable despite field-level sensor interference. WIM data from toll roads can also support structural risk assessment: a study using two WIM systems on Italian toll roads built a probabilistic vehicle load distribution model to assess bridge and road structural health [24]. , an approach adaptable in Indonesia to generate visualized infrastructure risk indicators for policymakers. Driver behavior also affects WIM accuracy; a YOLOv3 and Deep Residual Network-based method showed that vehicle speed and lateral position influence load-reading accuracy [25], suggesting the need to integrate visual camera data at weighing sites to validate WIM readings.

Beyond weighing systems, AI-based traffic monitoring and remote sensing offer further integration potential. A real-time framework combining computer vision, smartphone sensors, and GIS achieved high detection and tracking accuracy with low speed-estimation error relative to radar references [13], particularly relevant for cities with limited sensor infrastructure. Public transport vehicles can also serve as probe data collectors: GTFS-based real-time bus fleet data showed strong correlation with Bluetooth reference data and improved travel-time estimates [26], offering a supplementary data source for monitoring traffic around UPPKB locations.

Overall, comprehensive ODOL surveillance requires multiple complementary data layers, including dynamic WIM weighing data, visual camera data, AI/GIS-based location data, and probe vehicle data, consistent with the Intelligent Transport System (ITS) principle that data integration underpins an effective Traffic Big Data Platform for the formation of *Traffic Big Data Platform* that is able to support the DSS function optimally [2].

Table 2. Data Source Integration Patterns Identified from Literature Synthesis (RQ1)

Data Source	Technology	Detection Capability	Reliability Pattern	Key Limitation
WIM Static	Strain gauge / quartz sensor	Gross Vehicle Weight (GVW)	Stable over 15 months; re-verification every 8 months (Gajda et al., 2025; Ryguła et al., 2024) [22], [23]	Covers only 2.39% of passing vehicles (Asrib et al., 2026) [5]
Bridge WIM (BWIM)	Strain gauge on bridge structure	Axle load distribution	Data loss on sensor failure requiring regression-based reconstruction (Szinyéri & Kovari, 2026) [12]	Infrastructure-dependent; reconstruction adds uncertainty
ANPR + Deep Learning	YOLOv3 + Deep Residual Network	Vehicle identity, dimensions, driving state	Accuracy affected by speed/lateral position (Zhao et al., 2022) [25]	No load/weight data; needs WIM integration
AI + GIS Fusion	Computer vision + smartphone sensor + GIS	Vehicle density, speed, spatial location	High precision/recall, no systematic bias (Obaidat & Alomari, 2026) [13]	Cannot identify individual load/plate
Probe Vehicle (GTFS)	GPS IoT on transit fleet	Traffic speed proxy	High correlation with Bluetooth reference (Jiang et al., 2025) [26]	Cannot detect individual load/violation
WIM Direct Enforcement	Accuracy mapping	Legally defensible overload classification	Minimizes false-positive misclassification (Gajda et al., 2023) [11]	Requires periodic recalibration
Vision-Corrected WIM	Camera + piezoelectric sensor fusion	Gross weight under dynamic load	Improved accuracy for large wheel oscillations (Hagmanns et al., 2024) [35]	Limited gain for small oscillations

V-WIM (Vision-Based)	YOLOv8 + tire-deformation analysis	Vehicle weight without embedded sensors	Validated via component & on-site tests (Lam et al., 2025) [40]	Sensitive to image quality/lighting
Satellite + GIS	CenterNet + Mask R-CNN	Truck density across wide corridors	High spatial coverage incl. ports (Liu et al., 2024) [42]	No individual load/plate data

Analytic Design Principles for Multi-Stakeholder Visualization in ODOL DSS

Beyond identifying data sources, dashboard design must also determine how data is visualized for effective decision-making. Bivariate choropleth mapping, originally developed to compare public transport infrastructure impacts on travel time, allows two variables to be presented on a single map rather than two separate views [29], a technique directly adaptable to simultaneously display load violation and road damage levels. User-centered interactive dashboards also matter: an interactive map-based mobility dashboard demonstrated that placing users at the center of interaction improves data-driven decision-making, as validated through real-user usability evaluation [14], confirming that dashboard success depends not only on data completeness but on the interface's exploratory flexibility. Comparative visualization is equally relevant; a parallel coordinate plot (PCP) system for comparing transportation modes enabled query-based exploration and origin-destination mapping [30], adaptable for comparing ODOL violation rates across regions, vehicle types, or time periods.

Visualization can also interpret complex predictive outputs. A Shapley value-based visual analytics approach opened the "black box" of deep learning traffic predictions, helping decision-makers understand spatial and temporal influencing factors [27], directly relevant for presenting ODOL prediction results interpretably rather than as opaque probability scores. Similarly, a causal graph-based framework enabled interpretive representation of congestion patterns with customizable retrieval [31], adaptable for visualizing relationships among vehicle type, route, operational time, and violation rate.

Finally, combining centralized data repositories with visualization dashboards, as demonstrated for large-scale transportation data management [28], highlights the importance of separating data storage from visualization layers for modular system expansion. Collectively, the literature shows that dashboard effectiveness as a DSS depends on matching visualization technique to data characteristics and user needs, with bivariate maps, PCPs, and causal graphs each serving distinct comparison, exploration, and interpretation functions.

Table 3. Visualization Design Principles and Their Applicability to ODOL DSS (RQ4)

Visualization Technique	Analytic Design Principle	Stakeholder Level	ODOL DSS Application	Reference
Bivariate choropleth map	Multi-variable spatial encoding	Policy maker	Violation intensity + road damage on one map	Baltzer et al. (2024)
Interactive map-based dashboard	User-centered exploratory analytics	Analyst, field officer	Filter/explore violation spatial data	Delfini et al. (2024)
Parallel coordinate plot (PCP)	Cross-entity comparative analytics	Analyst	Compare violation rates across UPPKB areas	Deng et al. (2025)
Shapley-based visual analytics	Predictive model interpretability	Analyst, policy maker	Explain prediction variable contributions	Feng et al. (2024)
Causal graph representation	Pattern causality exploration	Analyst	Cause-effect between factors and violation rate	Nguyen et al. (2024)
Online data repository + dashboard	Centralized multi-source management	All levels	Modular data/visualization separation	Tsouros et al. (2024)
Satellite + GIS truck mapping	Wide-area spatial pattern detection	Policy maker, analyst	Macro-level corridor/port density monitoring beyond fixed sensors	Liu et al. (2024)

Interoperability Architecture Patterns for Cross-Agency Data Ecosystems

Beyond data sources and visualization, integrating heterogeneous data into a single functional DSS is central to this research. A decision support system for smart city security management, designed for seamless legacy-system integration, demonstrates how predictive evacuation models, threat assessment, and real-time traffic data can be aggregated into one coherent interface [15], a pattern directly relevant to Indonesia's fragmented ODOL data landscape (UPPKB, ANPR, toll-road WIM, traffic police records), where without an integration layer each system remains an isolated silo. This aligns with the Directorate General of Land Transportation's emphasis on connecting the MitraDarat dashboard with the JTO UPPKB system, BLUe data, and Regident Polri [9]. Sensor technology diversity presents further challenges; integrating computer vision, smartphone sensors, and GIS in one operational platform has been shown to produce consistent, unbiased outputs when properly validated [13]. confirming that multi-source integration need not compromise data consistency given adequate validation. Temporal and spatial synchronization is also essential: a platform combining online repositories with visualization dashboards for large-scale transport data required standardized data storage structures for consistent accessibility [28], underscoring the need for a dedicated data integration layer to standardize formats from UPPKB, WIM, and ANPR before visualization.

Multi-source integration can also close coverage gaps; GTFS-based real-time bus fleet data has been shown to complement fixed-sensor data on under-monitored roads [26], a principle applicable to patrol vehicle GPS data around UPPKB locations lacking permanent WIM infrastructure. Architecturally, this integration should follow a layered pattern separating data collection, integration/processing, and visualization layers, consistent with the Traffic Big Data Platform concept [2]. implemented via standardized API-based data exchange. Decision-support value also depends on serving multiple organizational levels, from field operations to ministerial policy, as demonstrated by Qatar's transport data repository and dashboard platform informing infrastructure, resource allocation, and safety decisions [28]. System resilience matters too: the same regression-based reconstruction approach addressing BWIM sensor failure [12] should be embedded at the integration layer with anomaly detection, ensuring the dashboard shows reliable estimates rather than blank or misleading data during sensor disruption. Predictive capability further strengthens proactive DSS function; a decision tree and Random Forest-based model for BRT congestion and travel-time prediction in Bandung, deployable on low-cost hardware [21], illustrates how historical movement data can predict high-risk overload locations and times, enabling more efficient resource placement.

In sum, an effective ODOL DSS platform requires an integration architecture accommodating data heterogeneity, ensuring consistency and continuity, supporting multi-level decision-making, and enabling predictive modeling, as inconsistency in any one aspect undermines visualization quality and user trust.

Comparative Perspectives on Heavy-Vehicle Overload Monitoring Across Countries

To enrich the contextual foundation of the proposed IOSD model, this study also examines how other countries manage the monitoring and enforcement of heavy-vehicle and overload violations. In Saudi Arabia, Automated Traffic Enforcement Systems (ATES), comprising speed cameras, red-light cameras, and mobile enforcement units, have proven effective in improving traffic compliance and reducing crashes, although the study emphasizes the need for ongoing evaluation of public perception and equitable enforcement [32]. This fully automated enforcement approach offers a useful comparative reference for Indonesia, which still relies heavily on selective manual inspection at UPPKB stations. In India, research on the impact of overloaded vehicles on asphalt pavement shows that the truck factor increases substantially with overload severity, rising by up to approximately 83 percent in extreme cases, prompting road authorities to tighten inspection protocols based on vehicle classification and pavement thickness [39]. This finding parallels conditions in Indonesia, where overloaded vehicles have similarly been shown to accelerate flexible pavement damage and increase national road maintenance costs [43].

In China, a study analyzing 1,862 overloaded truck related crashes on mountainous highways in Yunnan Province identified key factors contributing to injury severity, including road type, weather conditions, and seasonal variation, leading to recommendations for stricter commercial truck inspection and harsher penalties as mitigation measures [44]. This predictive, crash severity based analytical approach is relevant for adaptation within the analytics layer of IOSD, particularly for prioritizing high-risk locations by combining ODOL violation data with accident history. Meanwhile, in Brazil, research on barriers to ICT adoption in road freight transportation management found that a lack of top management support and uncertainty regarding return on investment were the most significant obstacles to digitalizing logistics surveillance systems [36]. This finding underscores the importance of cross-agency institutional commitment as a precondition for the successful implementation of IOSD in Indonesia, reinforcing the recommendation discussed in the Conclusion of this study.

Taken together, these cross-country comparisons confirm that although the core enabling technologies, namely WIM, ANPR, and computer vision, are relatively similar worldwide, the effectiveness of their implementation is largely determined by institutional readiness, enforcement policy, and cross-agency data integration. This comparative insight reinforces the central argument of this study, that a holistic, cross-agency IOSD architecture is essential for the Indonesian context, rather than relying solely on the adoption of individual monitoring technologies in isolation.

Table 4. Data Integration Architecture Patterns and Scientific Design Principles (RQ2)

Integration Challenge	Architecture Pattern	Design Principle	Reference
Heterogeneous data formats across agencies	Standardized API data exchange layer	Format-agnostic ingestion with unified storage schema	Tsouros et al. (2023)
Sensor failure and data loss	Multivariate time-series regression-based signal reconstruction	Continuous data availability with transparency indicator	Szinyeri and Kovari (2026)
Limited infrastructure coverage	Probe vehicle data supplementation via GTFS	Complementary multi-layer coverage to close spatial gaps	Jiang et al. (2025)
Cross-agency system silos	Legacy system interoperability design	Modular connectors for UPPKB, BLUe, Regident Polri, and toll road WIM	Gonzalez-Villa et al. (2024)
Temporal and spatial data synchronization	Layered acquisition, analytics, and visualization architecture	Layer separation enabling independent module updates	Abdurachman et al. (2025)

Analytic and Predictive Design Principles for Reactive and Proactive ODOL Enforcement

This sub-chapter examines accuracy and reliability dimensions of each data-source technology, since DSS output quality depends directly on input quality. WIM accuracy is influenced by technical and operational factors: strain gauge and quartz sensors exhibit different stability characteristics under varying weather and road conditions, though both remain reliable over observation periods up to fifteen months [22]. , implying that sensor type should be considered when comparing dashboard data across UPPKB locations. Operationally, driver behavior also affects accuracy; deep learning-based detection of vehicle speed and position during weighing can inform per-measurement confidence indicators [25], allowing decision-makers to distinguish reliable data from data requiring further verification. AI and GIS-based monitoring offers a complementary, high-precision alternative, with validated systems showing low speed-estimation error and no systematic bias relative to manual field checks [13], making it viable for locations lacking permanent weighing infrastructure. System resilience is equally important: the regression-based reconstruction algorithm addressing BWIM sensor failure [12] can similarly prevent sudden data gaps in the dashboard during field disruptions.

Predictive reliability also matters: the decision tree and Random Forest-based BRT prediction model [21]. demonstrates that historical data-driven machine learning can reliably underpin ODOL violation-pattern prediction. Model interpretability is essential when complex deep learning predictions inform enforcement decisions; Shapley value-based visual analytics [27]. ensures decision-makers understand the analytical basis of predictions rather than treating them as an unexplained "black box." Finally, technical reliability alone is insufficient without legal compliance context: SEM-PLS research shows drivers' legal awareness significantly mediates the relationship between surveillance technology and ODOL compliance [6], implying that IOSD should include non-technical features such as automatic compliance notifications to gradually build legal awareness among transport operators, functioning as an educational instrument alongside its monitoring role. In sum, each data-source technology has distinct accuracy characteristics and limitations, both technical (sensor variability, data loss) and operational (driver behavior effects), requiring the IOSD design to incorporate automatic correction mechanisms, confidence-level indicators, and data reconstruction capabilities so its outputs remain trustworthy for policy and enforcement decisions.

Table 5. Analytical Module Design Principles for ODOL DSS (RQ3)

Analytical Module	Design Principle	Scientific Basis	Output

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Violation detection module	Threshold-based classification against regulatory load and dimension limits	WIM and ANPR data fusion (Gajda et al., 2025; Zhao et al., 2022)	Real-time vehicle classification: compliant, minor violation, or gross violation
Spatial analytics module	Geospatial correlation of violation intensity with infrastructure damage	Bivariate multi-variable spatial encoding Baltzer et al. (2024)	Geographic distribution map of violation hotspots and road risk zones
Predictive ML module	Ensemble decision tree and Random Forest on historical vehicle movement data	Munadi et al. (2026)	Temporal-spatial risk map of high-probability future violation locations
Model interpretability module	Shapley value decomposition of prediction input variables	Feng et al. (2024)	Per-variable contribution display enabling accountable enforcement decisions
Infrastructure risk module	Probabilistic vehicle load distribution modeling per road section	Ravichandran et al. (2024)	Structural risk indicators per road section for maintenance prioritization
Data quality and confidence module	Confidence level indicator based on driving state at WIM crossing	Zhao et al. (2022)	Data reliability flag per measurement for enforcement action validation

Design of Integrated Data Visualization Dashboard Model as Decision Support System for ODOL Supervision

Synthesizing the preceding sub-chapters, this section presents the Integrated ODOL Surveillance Dashboard (IOSD), an architectural synthesis comprising three interconnected layers: data acquisition and integration, analytics and processing, and visualization and user interaction.

Table 6. RQ-to-IOSD Layer Mapping: Scientific Framework Synthesis (RQ5)

RQ	Scientific Focus	IOSD Layer	Key Module / Component	Interface Level
RQ1 — Data Source Patterns	Multi-source data identification and integration patterns	Layer 1: Data Acquisition and Integration	Multi-source ingestion, API standardization, data reconstruction	Backend (all levels)
RQ2 — Integration Architecture	Interoperability and cross-agency data consolidation	Layer 1: Data Acquisition and Integration	Unified data schema, legacy system connectors, temporal-spatial synchronization	Backend (all levels)
RQ3 — Analytic Design Principles	Violation detection, prediction, spatial analytics, interpretability	Layer 2: Analytics and Processing	Violation detection, ML prediction, Shapley interpretability, infrastructure risk	Analyst, policy maker
RQ4 — Visualization Patterns	Multi-stakeholder visualization design principles	Layer 3: Visualization and Interaction	Choropleth map, PCP, causal graph, Shapley visual analytics	All levels (frontend)
RQ5 — Interface Hierarchy	Role-based hierarchical interface design synthesis	Layer 3: Visualization and Interaction	Role-based access for field officer, analyst, and policy maker views	Field officer, analyst, policy maker

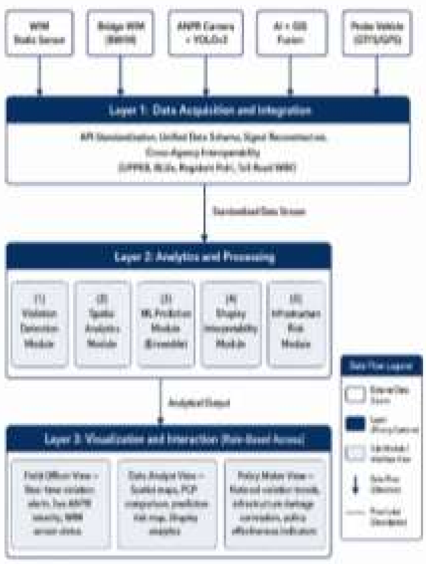

Figure 3. Three-Layer Functional Architecture of the Integrated ODOL Surveillance Dashboard (IOSD) with Inter-Component Data Flow

Layer 1 (Data Acquisition and Integration) aggregates WIM data from UPPKB and toll roads, ANPR camera data, AI-based computer vision data, GIS spatial data, and traffic police violation history. Given differing formats and update frequencies, this layer requires a standardization mechanism similar to Qatar's centralized transport data repository [28], converting inputs into a unified API-based format, and incorporates automatic data reconstruction to address BWIM sensor failure [12], displaying estimates with transparent indicators to preserve user trust.

Layer 2 (Analytics and Processing) comprises five modules: a violation detection module classifying vehicles against regulatory thresholds; a spatial analytics module using bivariate visualization to jointly map violation intensity and road damage [29]; a predictive machine learning module using decision tree and Random Forest approaches, as validated for Bandung's BRT system, to forecast high-risk locations and periods; a model interpretability module applying Shapley value decomposition to explain prediction drivers; and an infrastructure risk module applying probabilistic load distribution modeling, as demonstrated on Italian toll roads [24], to prioritize road maintenance.

Layer 3 (Visualization and User Interaction) presents analytics outputs through a user-centered, role-based interface [14], differentiated across field officers at UPPKB, analysts at the Directorate General of Land Transportation, and policymakers at ministry and police levels. Field officers receive real-time actionable information, including violating-vehicle lists with ANPR identity data, live position maps, repeat-offender alerts, and sensor status indicators.

Figure 4. Wireframe of the IOSD Operational Dashboard for Field Officers at UPPKB Weighbridge Stations

The interface prioritizes simplicity and rapid visual interpretation, consistent with feasible national-scale operational designs shown in real-time density mapping research[13]. Analysts access comprehensive filterable spatial violation maps, comparative time-series graphs, predictive visualizations with interpretability outputs, and query-based exploration.

Figure 5. Wireframe of the IOSD Analytics Dashboard for Data Analysts at the Directorate General of Land Transportation

Parallel coordinate plot comparisons, as developed for multimodal transportation quality comparison, can be adapted here to compare ODOL violation rates across UPPKB work areas. Policymakers receive long-term aggregated data supporting evidence-based policy formulation, including annual violation trends, damage-accident correlation maps, intervention effectiveness indicators, and projected infrastructure costs, consistent with Qatar's policy-level dashboard application informing infrastructure, resource allocation, and safety decisions. In the Indonesian context, this display can be a strategic instrument for the Ministry of Transportation, the National Police Corps, and the Ministry of Public Works to align intervention priorities and optimize cross-agency supervision budgets. A proactive notification feature also extends the dashboard beyond monitoring into compliance communication, automatically alerting freight operators of detected violations, consistent with SEM-PLS findings that legal awareness mediates the technology-compliance relationship and that combining surveillance with direct communication may be more effective than enforcement alone.

Effectiveness should be assessed across four dimensions: data coverage completeness (integration of WIM, ANPR, AI camera, and GIS data without significant gaps); detection and prediction accuracy; interface usability, in line with real-user evaluation approaches in urban mobility dashboard development; and operational impact, such as increased violation detection, faster enforcement response, and more efficient field resource placement.

The IOSD model's novelty lies in three aspects: it is the first model among the **thirty** literature analyzed to specifically contextualize transportation data visualization and multi-source integration for Indonesian ODOL surveillance; it integrates predictive and interpretive analytics rarely combined in a single platform, enabling both reactive and proactive function; and it is explicitly role-differentiated across field officer, analyst, and policy-maker levels, an approach not previously developed in documented ODOL surveillance literature. In summary, IOSD offers a technically coherent and practically implementable architectural framework for ODOL supervision in Indonesia, integrating diverse data sources, analytics modules, and role-tailored visualization. Its success ultimately depends on cross-agency commitment to open data access, consistent with the Directorate General of Land Transportation's urgency in connecting the MitraDarat dashboard, JTO UPPKB system, BLUe data, and Regident Polri into a unified digital enforcement ecosystem.

Conclusion

This study set out to answer five hierarchically structured research questions concerning the design of an integrated data visualization dashboard as a Decision Support System for ODOL surveillance in Indonesia. In response to these questions, the synthesis identified the critical data sources and interoperability patterns required for real-time violation detection, namely WIM, ANPR, AI-based computer vision, and GIS data; formulated the integration architecture and interoperability mechanisms necessary to consolidate these heterogeneous sources into a coherent platform; established the analytic and predictive design principles, including violation detection logic, machine learning-based prediction, spatial analytics, and model interpretability, needed to support both reactive and proactive enforcement; identified the visualization design patterns capable of communicating multi-dimensional surveillance outputs to varied stakeholders; and proposed a hierarchical interface structure reflecting the differentiated information needs of field officers, data analysts, and policymakers. These responses collectively converge into the Integrated ODOL Surveillance Dashboard (IOSD), a three-layer conceptual architecture comprising data acquisition and integration, analytics and processing, and visualization and interaction.

Beyond addressing an immediate operational concern, this study carries broader scientific and practical significance. Theoretically, it contributes a synthesized conceptual model that bridges previously fragmented strands of literature, sensor-based weighing technology, AI-driven traffic surveillance, and dashboard-oriented decision support design, into a single coherent framework tailored to a transportation-enforcement context that has not been systematically addressed in prior research. Its originality lies in the explicit role-differentiation of its interface architecture and in its integration of predictive and interpretive analytics within one platform, an architectural principle rarely combined in existing surveillance-system studies. Practically, the model offers the Ministry of Transportation, the National Police Corps, and the Ministry of Public Works a structured technical reference for advancing cross-agency digital transformation, with the potential to inform more transparent supervision practices, more efficient allocation of road maintenance budgets, and a stronger evidentiary basis for enforcement policy.

Nonetheless, this study is subject to several limitations that warrant acknowledgment. As a literature-based synthesis, the proposed IOSD model remains conceptual and has not undergone empirical testing, field deployment, or validation against real operational data from UPPKB stations. The literature corpus, while systematically selected through the PRISMA protocol, was limited to Scopus-indexed publications between 2022 and 2026, which may not capture all relevant regional practices or unpublished institutional reports. Future research is therefore encouraged to develop and pilot-test a functional IOSD prototype under actual field conditions, involving field officers, analysts, and policymakers as active participants in usability and performance evaluation. Subsequent studies may also examine cross-agency data governance mechanisms, long-term system scalability, and the institutional and regulatory adjustments required to sustain an integrated, real-time ODOL surveillance ecosystem in Indonesia.

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