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Auditable on-board diagnostics data validation for low-cost wireless vehicle telematics

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ABSTRACT

Low-cost wireless On-Board Diagnostics II (OBD-II) interfaces make vehicle telematics easier to access, but application fields cannot automatically be treated as valid diagnostic evidence. Support status, schema mapping, units, and asynchronous sampling may be unreliable. This study proposes an auditable rule-based validation layer that combines schema repair, source classification, parameter-eligibility checks, operating-window segmentation, descriptive t-based intervals, threshold sensitivity, cross-parameter plausibility, and expert review. A 2017 Toyota Avanza Type G was evaluated in three 106.071-s windows with 1,082 idle, 1,072 transition, and 1,083 near-constant-speed rows. Twelve indicator types remained suitable for retained or conditional use across all windows. Oxygen Sensor 1 was retained during idle and transition but assigned verify/exclude in cruise because it exactly duplicated a fuel-trim field and contained non-voltage values. Retained signals showed coherent load response, near-stoichiometric fuel control, stable dynamic coolant temperature, and module voltage near 13.9 V. All five expert-reviewed decisions reached majority acceptance, and four reached full consensus. The architecture provides traceable retain, conditional, exclude, and verify states before maintenance interpretation and supports safer, low-cost telematics for automated maintenance.

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1. INTRODUCTION

In robotics, automated maintenance, and Industry 4.0 systems, sensor data are useful only if the acquisition layer can separate valid measurements from interface errors [1]–[3]. Vehicle electronic control units (ECUs) and On-Board Diagnostics II (OBD-II) interfaces provide speed, engine RPM, airflow, throttle, temperature, fuel-trim, oxygen-sensor, and electrical data for telematics-based maintenance screening [4]–[7]. This study uses a 2017 Toyota Avanza Type G as a representative gasoline MPV case [8]. Recent hardware-in-the-loop work on an Avanza ECU also shows the continued value of low-cost off-board diagnostic methods [9]. Manufacturer guidance is used only as vehicle-specific context, not as a universal fault threshold [10].

OBD-II has developed from manual scan tools into wireless fleet platforms, smartphone applications, web monitoring, and remote analytics [11]–[14]. However, diagnostic standards define access methods and parameters; they do not ensure that every field shown by a low-cost application is supported,

correctly mapped, or meaningful for a specific ECU [5], [6], [15]. Sequential smartphone polling can also produce sparse and asynchronous samples. Exported files may contain missing or Infinity values, constant-zero outputs, duplicated fields, or malformed comma-separated-value (CSV) structures [7], [11]–[14].

Recent work covers OBD-based fuel and emission estimation, condition monitoring, data repair, low-cost logging, and predictive maintenance [16]–[21], [22]–[26]. These studies show that model quality depends on data availability and preprocessing, while automated-vehicle research separately emphasizes sensor-anomaly detection [27]. The unresolved front-end problem is that scanner-readable inputs are often accepted before their source, support status, schema integrity, and physical meaning are explicitly classified.

This study addresses this gap with a deterministic front-end validation architecture. It checks schema integrity, data source, PID eligibility, operating state, statistical behavior, cross-parameter plausibility, and expert safeguards. Unlike prior OBD-II studies that usually handle input validity within preprocessing or downstream models, this workflow makes field eligibility an explicit and auditable output. Before maintenance interpretation, each scanner output is assigned to one of four states: retain, conditional, exclude, or verify. This traceability is useful for safety-conscious fleet telematics, robotic platforms, and automated workshops because unsupported or mislabelled variables should not enter supervisory decisions [22]–[24], [25]–[27].

The objectives are to: i) design an auditable rule-based validation architecture; ii) provide a reproducible treatment of asynchronous polling and CSV misalignment; iii) characterize retained parameters during idle, 0-to-60 km/h transition, and near-constant-speed operation using descriptive confidence intervals and threshold sensitivity; and iv) map validated evidence to conservative maintenance screening evaluated against structured automotive-expert review.

2. PROPOSED RULE-BASED VALIDATION WORKFLOW

The architecture inserts a deterministic sequence of validation gates between wireless acquisition and maintenance interpretation (Figure 1), followed by a human-in-the-loop safeguard. Each output remains traceable to the rule and evidence that produced it, reducing the risk that unsupported, anomalous, or mislabelled fields propagate into maintenance decisions [12], [25]–[27].

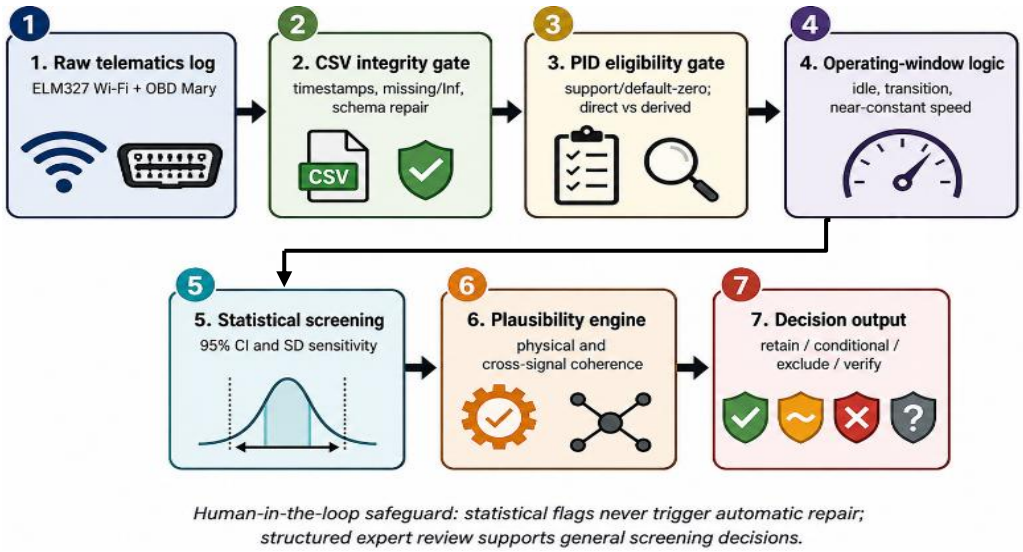


Figure 1. Auditable OBD-II validation architecture: integrity, PID eligibility, operating-window, statistical, plausibility, and decision gates produce retain/conditional/exclude/verify states before expert-supported screening

Algorithm 1. ECU-parameter validation and maintenance-screening logic
Input: raw OBD-II CSV logs, window definitions, candidate fields.
1) Audit timestamps, missing/Inf values, units, schema, and exact duplicates.
2) Repair split/misaligned fields.

3) Classify direct vs application-derived variables; retain plausible supported signals and verify/exclude default, duplicated, or implausible outputs.
4) Analyze each PID at its own timestamps within idle, transition, and cruise windows; no row-wise imputation.
5) Report mean, standard deviation (SD), descriptive 95% t-intervals and ±1.5/±2/±3 SD alert sensitivity; evaluate cross-parameter coherence.
6) Map evidence to monitor/inspect/verify actions; no alert alone triggers component replacement.
Output: validated parameter matrix and conservative maintenance-screening action.

3. METHOD

3.1. Research design and case platform

A single-case empirical design [28], [29] was used to evaluate the workflow on a 2017 Toyota Avanza Type G with a 1.329 L gasoline engine and manual transmission. Only generic emissions-related OBD-II fields were included; manufacturer-specific PID maps were outside the study scope. The processed export contained one timestamp and 43 parameter or application fields. It did not contain a Mode 01 support bitmap, raw request-response frames, ECU calibration identifiers, or adapter firmware identifiers. PID eligibility was therefore inferred from data availability, non-default responses, unit and schema integrity, operating-state plausibility, and cross-parameter coherence [5], [6]. Data were acquired with an OBD2 Wi-Fi V1.5 ELM327 adapter (PIC18F25K80), OBD Mary v1.248, and a Redmi Note 13 running Android 15/HyperOS 2.0.210.0.

To compare baseline and validated data, this study used a structured within-log baseline-to-validated design. The baseline was the application export as displayed, while the validated condition was the same export after integrity, source, eligibility, operating-state, statistical, and plausibility checks. This proof of concept evaluates ECU-accessible telematics and does not provide replicated fault diagnosis or universal MPV thresholds.

3.2. Wireless acquisition and operating windows

The dynamic log was recorded on May 3, 2026 (16:04-16:17 WIB) on a toll-road section in Malang Regency; a separate no-load idle log was recorded on May 11, 2026 (08:46-08:56 WIB). Ambient temperature was about 27-31 °C, Pertalite gasoline was used, and tire pressures followed the manufacturer recommendation [10]. Three nominal 106.071-s windows were extracted: idle 08:55:00.312-08:56:46.383 (1,082 rows), transition 16:06:23.596-16:08:09.667 (1,072), and near-constant speed 16:08:09.667-16:09:55.738 (1,083). Because PID polling was sequential, observed first/last timestamps could fall about 0.22 s inside nominal boundaries; no temporal interpolation was used.

3.3. Asynchronous polling, CSV repair, and data-quality control

OBD Mary polled enabled PIDs sequentially, so most rows contained only one non-null field. Each PID was analyzed at its own valid timestamps. Interpolation and multivariate row-wise imputation were not used. Cross-parameter coherence was assessed only at the operating-window level to avoid false time alignment between PIDs [7], [12], [21]. Frequency-domain cross-signal correlation was also not used because the sequential polling did not provide synchronized channels or stable sampling intervals. Under these conditions, phase or correlation estimates could be misleading and would not improve technical validity.

The principal schema error was the header “Oxygen Sensor 1, Short Term Fuel Trim,” whose internal comma split the field and shifted later labels. The repair recombined the field and realigned downstream columns against the corrected acceleration schema. A second audit found that cruise “Oxygen Sensor 1” exactly duplicated the O2/STFT field at all 36 paired samples (maximum difference 0), with -3.906% to 4.688% values rather than voltage; it was therefore assigned verify/exclude status. Missing/Infinity outputs were retained as audit evidence but excluded from fault interpretation.

3.4. Parameter eligibility and plausibility rules

Eligibility required availability, generic-service support evidence, physical plausibility, operating-state response, and cross-signal coherence [4]–[7], [15], [25]–[27]. Expected stability (e.g., zero speed at idle) was allowed. In contrast, outputs that were constant zero, duplicated, blank, or inconsistent in unit were assigned verify/exclude status when they did not match expected engine operation. Application-derived fuel variables were used only as consistency indicators rather than direct fuel-flow measurements [16], [30].

3.5. Statistical screening, confidence intervals, and sensitivity

For each eligible PID/window, mean and sample SD were reported with a conventional two-sided 95% t-based interval, $\bar{x} \pm t(0.975,n-1)s/\sqrt{n}$ [31], [32]. Because consecutive observations may be correlated, these

intervals describe only the sampled windows and should not be generalized to a larger population. ±2 SD was the main alert gate and was compared with ±1.5 and ±3 SD; pooled flag rates used only technically eligible observations. The ±2 SD level was selected as a pragmatic midpoint between the more sensitive ±1.5 SD and the more conservative ±3 SD screening levels; all three thresholds were retained to evaluate robustness.

3.6. Expert agreement and safe deployment

Three automotive practitioners independently reviewed parameter classification, anomaly interpretation, and maintenance-screening decisions using structured sheets. One validator was also a co-author, so this is structured technical validation rather than external blinded validation. Five consolidated decisions covered parameter suitability, treatment of unreadable PIDs, persistent-fault evidence, follow-up service, and the boundary between screening and final diagnosis. A decision was accepted at ≥2/3 agreement and reported by vote count, full consensus, observed/expected agreement, and Fleiss' κ [33]–[35]. Statistical alerts or questionable fields could not trigger replacement without repeated logging, DTC confirmation, professional scanning, or physical inspection [36], [37].

4. RESULTS AND DISCUSSION

4.1. Data quality and baseline-to-validated disposition

Across the three windows, core PIDs contained only 30-36 valid observations because sequential polling produced sparse samples for each PID. Schema repair restored the intended O2/STFT mapping. The cruise audit also found a field that was numerically complete but had the wrong meaning because it duplicated another field. Table 1 summarizes how the baseline application data changed after validation. A field was never treated as diagnostically valid only because it appeared in the application.

Table 1. Baseline-to-validated evidence disposition

Stage	Evidence	Validation outcome
Application baseline	The export contained 43 parameter or application fields; their presence and numeric values were visible in the application.	No field was treated as valid only because it was displayed.
Integrity/source gates	The split CSV header was repaired; missing/Inf values, default zeros, unit inconsistencies, and exact duplicates were classified.	Repair when the mapping is traceable; otherwise verify/exclude.
Eligible across all windows	Twelve indicator types: speed, RPM, throttle, MAF, time-based fuel use, derived power, coolant, intake-air temperature, Bank 1 STFT/LTFT, module voltage, equivalence ratio.	Retain or conditional use within observed operating range.
Window-specific O2	Oxygen Sensor 1 behaved as voltage in idle/transition but exactly duplicated O2/STFT in cruise.	Retain in idle/transition; verify/exclude in cruise.
Unsupported/undefined	Bank 3 trims, Lambda 2, injection/initial/oil-temperature fields, and distance-based fuel average at idle/early trip.	Treat as a data-acquisition or data-quality limitation, not as evidence of a vehicle fault.

4.2. Operating-window behavior and uncertainty

Figure 2 summarizes the three operating windows; speed is shown only at speed-PID timestamps, with no multichannel interpolation. Table 2 summarizes the mean, SD, descriptive 95% t-interval, and validity status of representative PIDs. The results show a stable idle condition and coordinated increases in load-related variables during transition. Cruise O2 is not reported numerically because the field failed the schema-integrity check, while fuel-use and power values remain application-derived indicators. Cross-parameter coherence is claimed only within the observed range, which reached 3004 rpm.

Bank 1 trims remained near zero and commanded equivalence ratio near 1.00. O2 Sensor 1 showed switching-type voltage in idle and transition, but the cruise field was excluded as an exact duplicate. Thus no persistent lean/rich anomaly was evident in retained signals, while the cruise conclusion relies on trims/equivalence ratio rather than O2 voltage. Dynamic coolant stayed about 82-85 °C and module voltage near 13.9 V; these windows did not assess warm-up time or complete cooling-system performance [4], [10].

4.3. Cross-parameter coherence and threshold robustness

Figure 3 compares normalized window means in Figure 3(a) and coefficients of variation in Figure 3(b) without implying synchronized timestamps. Load-related variables rose from idle to transition, and variability was highest during transition, supporting operating-state segmentation before statistical screening.

The eligible-observation counts were 394 for idle, 456 for transition, and 432 for cruise. Pooled flag rates at ±1.5 SD were 8.63%, 10.09%, and 11.57%; at ±2 SD, 1.02%, 4.82%, and 3.01%; and at ±3 SD, 0.00%, 1.32%, and 0.23%, respectively. Figure 4 shows that ±2 SD gives a middle level of alert sensitivity for this dataset. The transition window produces more flags because it includes a real physical transient. The

experiment did not include confirmed fault and no-fault ground truth, so these percentages are alert rates, not false-positive or false-negative rates.

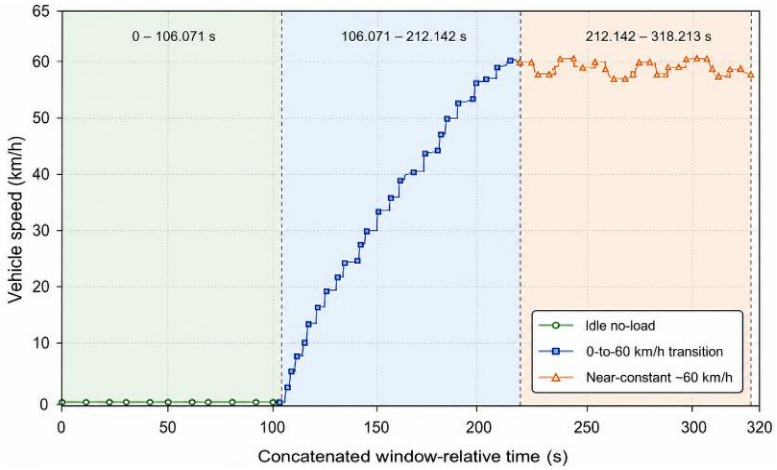
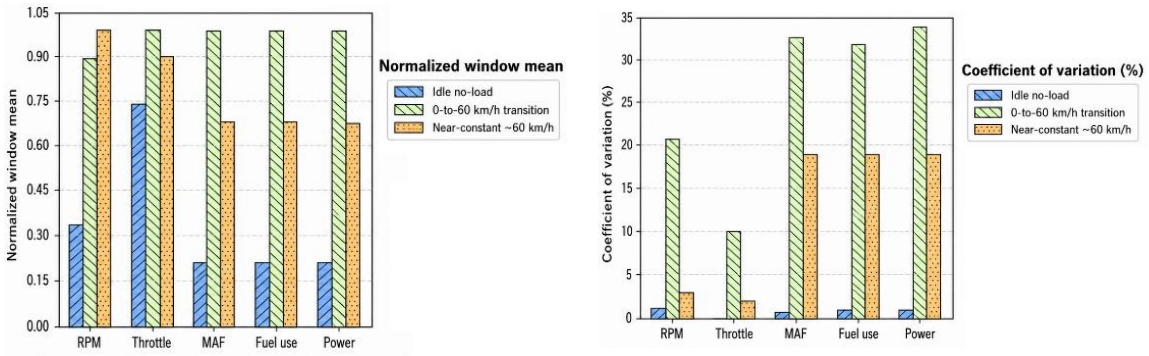


Figure 2. Operating-window segmentation for idle, 0-to-60 km/h transition, and near-constant-speed operation; PID-specific speed samples remain asynchronous and define the state windows used by the automated validation workflow

Table 2. Representative PID statistics and descriptive 95% t-based intervals

Parameter	Idle	Transition window	Near-constant 60 km/h	Status
Speed (km/h)	0.00 ± 0.00 | [0.00, 0.00]	38.58 ± 15.81 | [33.23, 43.93]	57.97 ± 1.59 | [57.43, 58.51]	Valid
Engine RPM	634.60 ± 9.22 | [631.16, 638.04]	2363.00 ± 493.84 | [2193.36, 2532.64]	2619.22 ± 66.73 | [2596.64, 2641.80]	Valid
Throttle (%)	17.25 ± 0.00 | [17.25, 17.25]	23.53 ± 2.23 | [22.76, 24.30]	21.57 ± 0.66 | [21.34, 21.79]	Valid
MAF (g/s)	1.65 ± 0.03 | [1.64, 1.66]	10.68 ± 3.64 | [9.42, 11.93]	7.01 ± 1.32 | [6.57, 7.46]	Valid
Coolant (°C)	74.57 ± 1.17 | [74.13, 75.00]	84.03 ± 0.98 | [83.69, 84.37]	82.97 ± 0.17 | [82.92, 83.03]	Valid
Intake air (°C)	32.33 ± 0.71 | [32.07, 32.60]	44.09 ± 1.15 | [43.69, 44.48]	41.36 ± 0.83 | [41.08, 41.64]	Valid
STFT Bank 1 (%)	-1.64 ± 0.90 | [-1.98, -1.30]	-0.45 ± 2.58 | [-1.33, 0.44]	-0.39 ± 2.28 | [-1.16, 0.38]	Valid
LTFT Bank 1 (%)	-5.47 ± 0.00 | [-5.47, -5.47]	-1.27 ± 1.93 | [-1.94, -0.61]	0.07 ± 0.76 | [-0.19, 0.32]	Valid
Oxygen Sensor 1 (V)	0.44 ± 0.27 | [0.34, 0.54]	0.48 ± 0.30 | [0.38, 0.59]	Excluded: exact duplicate of O2/STFT fuel-trim field	Valid in idle/ transition; verify/ exclude in cruise
Voltage (V)	13.93 ± 0.02 | [13.93, 13.94]	13.91 ± 0.07 | [13.88, 13.93]	13.95 ± 0.02 | [13.95, 13.96]	Valid
Equivalence ratio	1.001 ± 0.000 | [1.001, 1.001]	1.001 ± 0.000 | [1.001, 1.001]	1.001 ± 0.000 | [1.001, 1.001]	Valid



(a) (b)

Figure 3. Cross-parameter evidence: (a) normalized window means and (b) coefficient of variation. Patterns distinguish windows; PID-specific samples are not synchronized

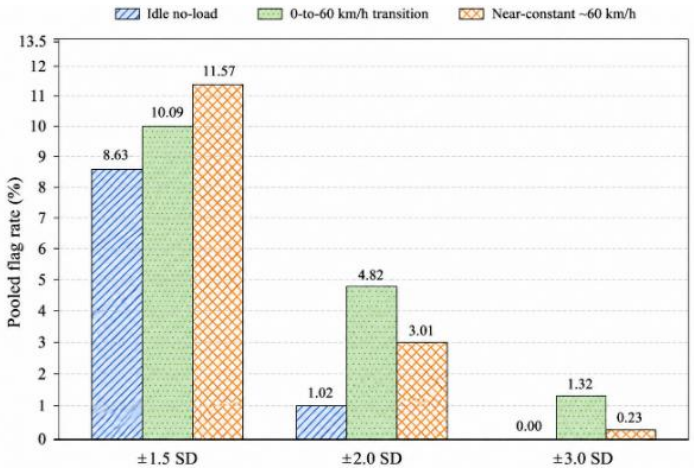


Figure 4. Statistical-alert sensitivity at ±1.5, ±2.0, and ±3.0 SD. The comparison supports threshold selection for automated screening; cruise O2 is excluded after schema-integrity failure, and flags are not automatic faults

4.4 . Parameter validity and scanner-artifact implications

Parameter validity depended on evidence rather than field presence in the application. The cruise O2 duplication demonstrates that a numerically complete but semantically inconsistent field should trigger PID/scanner verification rather than vehicle-fault inference [5], [6], [15]. Table 3 summarizes the resulting validity decisions and maintenance implications.

Table 3. Parameter-validity decisions and maintenance implications

Parameter group	Retained or excluded variables	Observed evidence	Decision and implication
Performance/load	Speed, RPM, throttle, MAF	Coherent with operating state	Retain for load/state screening
Derived indicators	Fuel use, instant power	Follow load; application-calculated	Conditional only
Air-fuel	STFT/LTFT B1, equivalence ratio; O2 idle/transition	Trims near 0; ratio ~1; cruise O2 duplicated	Retain with cruise O2 verify/exclude
Thermal/electrical	Coolant, IAT, module voltage	Plausible trends; ~13.9 V	Retain for trend screening
Unsupported PIDs	Bank 3 trims, Lambda 2	Constant zero/default	Audit trail; verify/exclude from faults
Undefined fields	Injection/initial/oil temp; idle distance fuel avg	Zero, missing, or Infinity	Data-quality limitation; no repair inference

4.5. Expert agreement

All five general decisions achieved majority acceptance; four reached full 3/3 consensus, and 14/15 ratings were “Agree” (Table 4). One validator requested additional confirmation above approximately 3000 rpm, so the coherence claim is limited to the observed 3004-rpm range. Observed agreement was 0.867, expected agreement was approximately 0.876, and Fleiss’ κ was approximately −0.071. Because ratings were highly concentrated, vote counts and full-consensus rates are more informative for this small matrix. Minor descriptive values changed after the final schema audit, but the five consolidated screening decisions were unchanged. The later cruise O2 duplication was not re-rated by the validators.

Table 4. Expert agreement on summarized validation decisions

Reviewed aspect	Decision	Interpretation used in manuscript
Main ECU parameters suitable for screening	3/3	Retain within observed range; confirm >3000 rpm
Constant-zero/unreadable PIDs excluded from fault interpretation	2/3	Keep visible as verify/exclude; professional scan if needed
No strong persistent fault evidence	3/3	Window-limited screening only
Periodic service/conditional follow-up	3/3	Further inspection if symptoms/DTC/repeated abnormal logs
Screening, not final diagnosis/replacement	3/3	No autonomous corrective-repair claim

4.6. Originality, comparison with prior work, and automation relevance

Prior OBD-II studies span telematics acquisition, fuel/emission estimation, predictive or anomaly-oriented diagnostics, and more recently automated fault diagnosis and report generation. Unlike these studies,

the present work makes parameter eligibility a traceable output of the front-end validation step. The validation gates detected missing or default values, CSV shifts, and an exact duplicate field with an incorrect label and unit. Table 5 contrasts these streams with the proposed front-end architecture.

Table 5. Position relative to established OBD-II research

Approach	Typical objective	Usual validity treatment	Contribution of this study
Wireless/remote telematics [11], [13], [14], [17], [21], [38]	Acquire/transmit variables	Availability/communication checks	Adds field-level eligibility/ schema/ duplicate decisions
Fuel/emission estimation [16], [18]–[20], [26], [30], [39], [40]	Estimate consumption/ emissions	Cleaning/model validation	Separates direct, derived, and mislabelled fields
ML/predictive diagnostics [12], [22]–[24], [25]–[27], [41]	Predict/classify/report	Input validity commonly handled within preprocessing/model-development workflows	Adds an explicit auditable front-end eligibility gate before downstream modeling.
This architecture	Validate scanner outputs	Integrity, support, state, sensitivity, coherence, expert safeguard	Retain/conditional/exclude/verify states

For fleet condition-based maintenance, the four states can act as a gate between low-cost telematics data and maintenance rules. Retained signals can enter trend analysis, conditional fields need context, and verify/exclude fields remain visible for audit but cannot trigger automatic repair decisions. The same principle can be useful in robotics and manufacturing automation because embedded controllers, mixed sensor systems, wireless gateways, and supervisory maintenance services face similar risks from unsupported or mislabelled variables [1]–[3], [22]–[24], [25]–[27]. Transfer to AGVs, mobile robots, or automated workshop stations is claimed only at the architecture level because these platforms were not tested directly. The case is also suitable for teaching automotive electronics, robotics, and data validation because it shows that a readable scanner value is not always valid evidence.

4.7. Scope, limitations, and future work

The main limitations are the use of one vehicle, three short operating windows, one adapter and application, and three experts. The study did not include confirmed faults, manufacturer-specific PID interrogation, gas analysis, direct fuel-flow or dynamometer measurements, synchronized acquisition, or raw diagnostic frames. The t-intervals are descriptive, were not adjusted for serial correlation, and do not support replicate-level inference across vehicles or fault classes. The exact source of the cruise O2 duplication also cannot be identified uniquely. Future work should use multi-vehicle testing, hardware-in-the-loop validation, professional scanners, physical inspections, raw frames, PID-support bitmaps, gas or fuel-flow measurements, and synchronized acquisition for time-series or frequency-domain analysis. Long-term validation is required before predictive or autonomous maintenance claims, and low-confidence evidence should remain under technician supervision [22]–[24], [41], [42].

5. CONCLUSION

This study developed an auditable front-end validation layer for low-cost wireless OBD-II telematics using three 106.071-s operating windows. Twelve indicator types remained usable across all windows, while cruise Oxygen Sensor 1 was assigned verify/exclude because it duplicated a fuel-trim field. Retained signals showed coherent load response, near-stoichiometric fuel control, stable dynamic coolant behavior, and module voltage near 13.9 V. At ±2 SD, pooled alert rates were 1.02%, 4.82%, and 3.01% for idle, transition, and cruise. All five expert-reviewed decisions achieved majority acceptance. The main contribution is a reproducible architecture that converts scanner outputs into traceable retain, conditional, exclude, and verify states before maintenance interpretation. The single-vehicle results do not support autonomous repair decisions, but they provide a practical safety-oriented interface for low-cost telematics and a useful teaching case for automotive electronics, robotics, and sensor-data validation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest

INFORMED CONSENT

Validators voluntarily completed signed technical-review sheets; only aggregated judgments are reported, and no sensitive participant data were collected.

ETHICAL APPROVAL

Ethical approval was not required because no human/animal experiments or sensitive personal-data collection were performed; expert involvement was limited to professional technical assessment.

DATA AVAILABILITY

Processed OBD-II window datasets and processing documentation are available from the corresponding author upon reasonable request. Signed validator forms are subject to confidentiality.

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