

Multi-Sensor Fault-Aware Road-Safety Monitoring for Powered Vehicle: A Review and Proposed Framework

¹Saravanakumar R, ²Aishali Datta Chowdhury, ³Aeindrila Roy, ⁴Ananya Rajesh

¹Faculty Guide Professor Higher Academic Grad

¹²³Electronics and Instrumentation

Abstract Motorcycle and scooter riders are among the most vulnerable road users because they have little physical protection, limited rear-side awareness, and depend on timely emergency response after a crash. This paper reviews sensor-based Internet of Things (IoT) road-safety systems for powered two-wheelers, covering inertial crash and abnormal-motion detection, alcohol-vapour screening with low-cost gas sensors, blind-spot sensing, communication and alerting, and the detection of sensor and communication faults. It organises the field in a five-category taxonomy, compares the strengths and limits of the main sensing technologies, and examines recent patent filings to show how these functions are being combined in practice. The analysis points to recurring gaps: single-function designs, fixed thresholds, little reported validation, and few checks on whether the sensors and links themselves are working. To address these gaps, the paper proposes a conceptual fault-aware multisensor framework that validates data, confirms events using several conditions, and classifies sensor, communication and data-consistency faults before raising an alert. The framework has not yet been validated experimentally; a test protocol and open research problems are outlined.

Keywords— road safety, powered vehicle, Internet of Things, crash detection, alcohol sensing, blind-spot detection, sensor fault detection, sensor fusion

I. INTRODUCTION

Powered two-wheelers, including motorcycles and scooters, remain among the most vulnerable categories of road users. Riders have little physical protection and are directly exposed to collisions, falls, environmental hazards and errors of perception or judgement. Unlike enclosed vehicles, two-wheelers offer little space for safety instrumentation and depend heavily on the rider's ability to keep balance, observe surrounding traffic and react promptly [1]. Risks arise from sudden impact, loss of control, impaired riding, limited rear-side visibility, delayed emergency response, and failure of the sensing or communication components of the electronic safety system itself.

Low-cost microcontrollers, inertial sensors, wireless communication and IoT platforms now make real-time road-safety monitoring practical [2].

Accelerometers and gyroscopes in inertial measurement units (IMUs) capture rapid changes in translational and rotational motion linked to harsh braking, abnormal manoeuvres, falls and possible crashes, and wearable inertial sensing is well established in fall-detection research[3]–[5]. These signals can be analysed through resultant acceleration, angular velocity, peak magnitude, root-mean-square (RMS) value, variance, rate of change, orientation change and post-event immobility. A high acceleration value alone does not prove a crash, however, because potholes, speed breakers, rough roads, sudden braking, aggressive turning and careless handling produce similar signatures. Reliable crash detection therefore requires multi-condition confirmation, such as combined analysis of acceleration, angular velocity, duration and post-event motion state.

Alcohol-impaired riding is another major concern because alcohol affects reaction time, judgement, coordination and risk perception. Low-cost semiconductor gas sensors such as the MQ-3 are

used in prototype and patented designs for detecting alcohol vapour [6], [7]. The MQ-3 uses a tin dioxide (SnO₂) sensing element whose electrical conductivity changes in the presence of alcohol vapour. Its output, however, depends on warm-up, calibration, temperature, humidity, ageing, airflow, placement and interference from other gases. MQ-3-based systems should therefore be treated as screening or warning mechanisms, not as certified breath-alcohol instruments, and a practical system must also distinguish alcohol in the rider's breath from alcohol-containing substances in the surroundings. Blind spots and poor rear-side awareness also contribute to risk during lane changes, overtaking, merging and turning. Blind-spot sensing warns when a vehicle, cyclist, pedestrian or other object enters a predefined rear-side zone. Infrared (IR) sensors offer a simple, low-cost option for short-range presence detection, but reflective IR sensing is affected by sunlight, rain, dust, target colour, reflectivity, angle and limited range, so IR alone may be insufficient for high-speed outdoor riding. Ultrasonic sensors, millimetre-wave radar, cameras, LiDAR and multisensory fusion offer other trade-offs in range, robustness, cost, computing demand and reliability.

Effectiveness depends on more than detection accuracy; it also depends on the reliability of the measurement and communication chain. Sensors can produce out-of-range values, drift, stick at a constant value, generate excessive noise or fail temporarily, and wireless links can lose packets, delay transmission or disconnect [8]. Unrecognised failures may cause false alerts, missed hazards, or a sensor malfunction being misread as a rider-related abnormal condition. For example, low variation in an accelerometer signal should not be read as a stationary vehicle if the gyroscope indicates continuing motion. Such cross-sensor consistency checking can reveal stuck-sensor faults and raise confidence in the final decision. Existing work usually treats these functions in isolation, such as crash detection, emergency alerting, alcohol sensing, blind-spot detection or vehicle tracking, and published reviews cover related but separate scopes, for example, active safety systems for powered two-wheelers [1] and smart helmets with multimodal

sensing [2]. To the authors' knowledge, no review yet examines crash and motion monitoring, alcohol screening, blind-spot sensing, IoT communication, sensor and communication fault detection, and alert reliability together. A safety decision should depend not only on sensor readings but also on the quality, consistency, and availability of those readings.

This paper therefore reviews sensor-based IoT road-safety systems for powered two-wheelers. Its objectives are:

- to examine sensing technologies for crash, fall, abnormal-motion, alcohol-impairment and blind-spot monitoring;
- to compare signal-processing, threshold-based, rule-based and intelligent classification approaches for real-time safety-event detection;
- to evaluate the suitability and limits of MQ-3 sensors for alcohol-vapour screening in road-safety prototypes;
- to compare IR sensing with ultrasonic, radar, camera, LiDAR and fusion-based approaches for blind-spot monitoring; and
- to propose a conceptual fault-aware multisensor framework that validates data, confirms events and classifies faults before an alert is raised.

The rest of the paper is organized as follows. Section II describes the review methodology, and Section III presents a taxonomy. Sections IV to VI cover motion, alcohol and blind-spot sensing. Section VII covers signal processing, decision logic and fault detection; Section VIII proposes the framework, and Section IX compares representative patent filings. Sections X to XII discuss challenges, future directions and conclusions.

II REVIEW METHODOLOGY

1. Review Design

This work is a scoping review that maps and critically analyses the literature on sensor-based road-safety technologies for powered two-wheelers, with a conceptual framework proposed from its findings. It covers systems that use sensing, embedded processing, IoT communication and decision algorithms to detect or mitigate road-safety risks. A

scoping design suits a topic with diverse technologies, study designs, sensor configurations, metrics and settings: rather than estimating

one pooled outcome, it identifies major concepts, compares technical approaches and maps gaps. Reporting follows the PRISMA 2020 statement [9] and its scoping-review extension, PRISMA-ScR [10], which set out how to define eligibility criteria, report information sources and search strategy, select studies, chart data and synthesise findings.

2. Review Questions

The review addresses five questions.

- RQ1: What sensing technologies are used in powered two-wheeler road-safety systems for crash detection, abnormal-motion detection, alcohol screening and blind-spot awareness?
- RQ2: Which signal-processing, threshold-based, rule-based, machine-learning and sensor-fusion methods classify safety-related events?
- RQ3: What are the strengths and limits of MQ-3 and related alcohol sensors for rider screening?
- RQ4: How do IR, ultrasonic, radar, camera, LiDAR and multisensory systems compare for blind-spot monitoring?
- RQ5: How are sensor faults, communication failures, false alarms, missed detections and environmental disturbances addressed?

3. Information Sources and Search Strategy

Literature is collected from IEEE Xplore, Scopus, Web of Science, ScienceDirect, SpringerLink and publisher databases, with Google Scholar as a supplementary source for citation trails and papers not indexed elsewhere. English-language studies from 2015 to October 2026 are considered because low-cost IoT controllers, MEMS sensors and embedded road-safety applications became common in that period. Search strings combine three concept groups with Boolean operators, for example: ("powered two-wheeler" OR motorcycle OR scooter OR "road safety") AND (IMU OR accelerometer OR "crash detection" OR "alcohol sensor" OR MQ-3 OR "blind spot" OR IoT) AND ("fault detection" OR "sensor fusion" OR alert). Strings are adapted to each database, and reference lists of review articles and highly relevant studies are screened for publications

the databases missed. The final search date, filters and complete database-specific strings are recorded in the supplementary material, as PRISMA recommends [9].

4. Eligibility Criteria

Studies are included if they (i) were published between 2015 and 2026; (ii) are peer-reviewed journal or conference papers in English; (iii) address at least one of crash or motion monitoring, alcohol detection, blind-spot detection, IoT communication for safety, or sensor and communication fault handling; and (iv) describe a method, system or evaluation in enough detail to analyse. Studies are excluded if they are editorials, theses or non-peer-reviewed web content, concern only in-cabin driver monitoring unrelated to these topics, or have no obtainable full text. Studies on four-wheeled vehicles are kept when their sensing or fault-handling methods apply directly to two-wheelers. Patent applications are not treated as evidence of performance; recent Indian filings are instead examined separately in Section IX as an indicator of how safety functions are combined in practice.

5. Study Selection

Records from all sources are merged and duplicates removed. Titles and abstracts are screened against the eligibility criteria, full texts of the remaining records are assessed, and reasons for exclusion at the full-text stage are recorded. The numbers at each stage are reported in a PRISMA flow diagram.

6. Data Extraction

A structured extraction sheet, pilot-tested on a small set of studies, records the author and year; country or context; vehicle or application; safety objective; sensor types; controller and communication method; algorithm or processing approach; experimental setting; sample size or test scenarios; evaluation metrics; reported performance; limitations; and future-work Rider and vehicle state Surrounding environment Communication and emergency response Intelligence and decision Reliability and fault awareness Impact, fall, abnormal motion, impairment Blind-spot and proximity warning, obstacle and road-surface sensing Alerts, location, dashboards, emergency messages Turn readings

into safety decisions. Check that sensors and links work. IMU, tilt, wheel-speed, GPS, pressure and alcohol sensors. IR, ultrasonic, radar, camera, LiDAR. ESP32, Bluetooth, Wi-Fi, cellular, MQTT, HTTP. Thresholds, rule-based logic, fuzzy logic, machine learning. Range and timeout checks, cross-sensor checks, self-test recommendations. Accuracy, sensitivity, specificity, precision, false-alarm rate, missed-detection rate, response time, detection range, communication latency, power consumption and environmental robustness are extracted whenever reported. For alcohol sensors, the calibration method, warm-up requirement, sensing range, environmental sensitivity and cross-sensitivity are also recorded. For blind-spot systems, the sensing range, field of view, detection reliability, speed suitability and performance in rain, darkness, sunlight or cluttered traffic are recorded.

3. Quality Assessment and Synthesis

Because the evidence is mostly engineering prototypes, formal clinical risk-of-bias tools are unsuitable. Each study is instead rated on five criteria adapted to this field: clarity of method, realism of testing (laboratory, simulated or on-road), size and description of the dataset, use of comparable metrics, and discussion of limitations. Each criterion scores 0 to 2, and low-scoring studies are retained but flagged in the comparison tables. Synthesis is thematic: studies are grouped by sensing function, mapped to the research questions and compared on sensors, methods, reported performance and fault awareness. Where tests differ so that numbers cannot be compared directly, the review describes trends and does not rank studies.

III. TAXONOMY OF SENSOR-BASED ROAD-SAFETY SYSTEMS

Sensor-based road-safety systems for powered two-wheelers can be classified by primary safety function, sensing modality, processing location, communication method and warning or intervention mechanism. No single sensor covers the motion of the vehicle, the condition of the rider, the surrounding road environment and the health of the measurement system, so a practical system needs several. Existing active safety systems for

motorcycles monitor vehicle behaviour or surrounding hazards and warn the rider before a dangerous situation develops, using radar, laser, infrared, cameras, inertial sensors or vehicle-to-vehicle communication [1]. Table I summarises the five categories used in this review.

1. Rider and Vehicle State Monitoring

The first category monitors the dynamic state of the vehicle and rider with accelerometers, gyroscopes, IMUs, tilt sensors, wheel-speed sensors, GPS modules, pressure sensors or alcohol sensors. Its purpose is to identify unsafe motion, rider impairment, possible collision, fall, loss of balance, over-speeding, or abnormal riding behavior. IMU-based monitoring is the most widely used approach and is detailed in Section IV; alcohol-impairment screening with semiconductor gas sensors is treated in Section V.

2. Surrounding Environment Monitoring

The second category observes objects, vehicles, lanes, road surfaces and hazards around the two-wheeler. Its functions include blind-spot monitoring, rear-side proximity warning, forward-collision warning, lane-change assistance, adaptive following-distance support, obstacle detection and road-surface monitoring. Blind-spot monitoring is especially relevant during lane changes, overtaking, merging and turning. The sensing region is usually at the rear-left and rear-right of the vehicle, where mirrors may not give complete visibility. Section VI compares the technologies used.

3. Communication and Emergency Response

The third category transmits safety information to the rider, an emergency contact, a dashboard, a cloud server or a traffic-management platform. Common technologies include ESP32-based controllers, Bluetooth, Wi-Fi, cellular links, MQTT and HTTP-based cloud services. They can send crash notifications, location, vehicle condition, alcohol-warning status, blind-spot alerts and diagnostic information. Low-cost prototypes combine impact sensing with GPS and GSM messaging for post-crash notification [6], while proximity sensors provide pre-crash warnings; other filings add hands-free wireless communication kits to rider equipment [11].

4. Intelligence and Decision Layer

The fourth category covers the algorithms that turn raw readings into safety decisions. The simplest use fixed thresh-olds: an acceleration magnitude above a preset level may trigger a crash candidate, and an object within a set distance may trigger a blind-spot warning. Thresholds are computa-tionally cheap but sensitive to sensor placement, calibration, riding style, road quality, vehicle type and environment. More advanced approaches use multi-condition rule-based logic, fuzzy systems, statistical methods and machine-learning mod-els. Learned models can adapt to riding patterns but need representative labelled data and more computing resources; one recent filing describes an on-board classifier trained on crash and motion data [12].

5. Reliability and Fault-Awareness Layer

The fifth category, often missing from existing designs, verifies that the sensors, power supply and communication link are working before a reading is trusted. Typical mechanisms are range and missing-data checks, communication timeouts, stuck-at detection, cross-sensor consistency checks, self-tests and calibration routines [8]. This layer is developed in Sec-tion VII-D.

IV. IMU-BASED CRASH AND ABNORMAL-MOTION DETECTION

IMUs are among the most widely used sensors for mon-itoring the dynamics of powered two-wheelers. A typical IMU combines a three-axis accelerometer and a three-axis gyroscope, measuring linear acceleration and angular velocity together. IMUs are compact, low-cost and light, and can be fitted to the vehicle body, the handlebar, a rider-worn device or an embedded IoT module. Impact and fall detection from IMU data follows the same signal-processing principles as wearable fall-detection research [3]–[5]. Because an impact may act along any axis, the resultant acceleration and resultant angular velocity are computed as

$$A_r = a_{x2} + a_{y2} + a_{z2}, \quad (1)$$

$$\omega_r = \omega_{x2} + \omega_{y2} + \omega_{z2}. \quad (2)$$

A crash-detection system extracts features from a moving window of IMU data. Common features include peak resultant acceleration, peak angular velocity, RMS acceleration, variance, standard deviation, jerk, orientation change, duration of the abnormal event and post-event immobility. The RMS acceleration over a window of N samples is

$$A_{RMS} = \sqrt{\frac{1}{N} \sum_{k=1}^N A_r^2(k)}, \quad (3)$$

and the rate of change of acceleration, called jerk, helps detect sudden events:

$$J(k) = \frac{A_r(k) - A_r(k-1)}{\Delta t}. \quad (4)$$

A large acceleration peak combined with high jerk may indi-cate a sudden impact. Detection based on a single acceleration threshold is unreliable, however, because normal riding also produces short spikes. Research therefore increasingly favours multi-condition event confirmation. In a rule-based system, a probable crash is declared only when several conditions hold together, for example

$$(A_{peak} > T_A) \wedge (\omega_{peak} > T_\omega) \wedge (t_{still} > T_s), \quad (5)$$

where T_A , T_ω and T_s are thresholds set from experimental baseline data and t_{still} is the post-event stationary period.

V. ALCOHOL DETECTION AND MQ-3 ASSESSMENT

Alcohol-impaired riding is an important road-safety concern because alcohol impairs reaction time, attention, coordination, judgement and risk perception. The MQ-3 is widely used because it is inexpensive, easily available and simple to interface with microcontrollers such as the ESP32 or Arduino. Two of the filings examined in Section IX use MQ-series sensors to block ignition when the alcohol level exceeds a preset threshold [6], [7].

In clean air the SnO₂ sensing layer has relatively high resistance. When alcohol vapour is present, the conductivity of the layer increases, changing the sensor resistance and output voltage, so the sensor gives an analogue response related to the alcohol-vapour concentration around it. In a prototype, the

output may be processed by baseline correction, calibration, thresholding and repeated sampling before a warning is generated.

A key limitation is that the raw output cannot be read directly as an exact blood-alcohol concentration or a legally valid breath-alcohol concentration. The response is affected by environmental alcohol sources, perfumes, sanitisers, cleaning fluids, fuel vapours, cigarette smoke, temperature, humidity and other cross-sensitive gases. An MQ-3-based design should therefore be described as an alcohol-vapour presence screening system, not as a certified breathalyser, forensic device or legal ignition interlock. Its role in a low-cost prototype is to identify a potential alcohol-related risk and trigger a warning, a log entry or a conditional safety response.

VI. BLIND-SPOT MONITORING TECHNOLOGIES

Blind spots are regions around a vehicle that cannot be adequately observed by direct vision or standard mirrors. For powered two-wheelers the risk is greatest during overtaking, lane changing, merging, turning and riding in dense traffic, when a rider may fail to notice a vehicle, cyclist, pedestrian or obstacle approaching from the rear side. Blind-spot monitoring detects objects in predefined zones and gives a visual, audible or haptic warning before the rider starts an unsafe manoeuvre. Table II compares the main sensing technologies qualitatively. Reflective IR sensors give fast, low-cost, short-range presence detection but are strongly influenced by ambient sunlight, object colour, reflectivity, angle, dirt and weather. Ultrasonic sensors add distance estimates at similar cost but are limited in range and affected by temperature, wind and

Table II
Qualitative Comparison Of Blind-Spot Sensing Technologies

Sensor	Range	Main weakness	Cost	Processing
Reflective IR	Short	Sunlight, target colour, rain, dust	Very low	Very low
Ultrasonic	Short	Temperature, wind, soft or angled targets	Low	Low
Radar	Medium	Cost, clutter and	High	Moderate

(mm-wave)	to long	multipath		
Camera	Wide field of view	Lighting, glare, dirt	Moderate	High
LiDAR	Medium	Heavy rain, fog, dust	Highest	High

target surface. Millimetre-wave radar offers longer range and relative-speed measurement and is less sensitive to light and rain, at higher cost. Cameras can classify vehicles, pedestrians and obstacles but depend on lighting and need more computation, and LiDAR gives precise three-dimensional ranging at the highest cost and processing load. One patented design uses a visor and rear cameras to show the rear view and adjusts the alert intensity with the distance of an approaching vehicle [7]. A meaningful assessment must compare these technologies rather than assume one low-cost sensor is suitable everywhere.

VII. SIGNAL PROCESSING, DECISION LOGIC AND FAULT DETECTION

1. Preprocessing and Noise Handling

Sensor data from IMUs, gas sensors, IR, ultrasonic and radar modules are often noisy, irregular or disturbed by the environment. Accelerometer data contain vibration from the engine, road and mounting, gyroscope data may show bias drift, and MQ-3 readings vary with warm-up, temperature, humidity and airflow. Each reading can be modelled as the true signal plus noise,

$$x_m(t) = x(t) + n(t), \quad (6)$$

and noise is reduced by moving-average, low-pass or median filtering. A moving average of length N is

$$y(k) = \frac{1}{N} \sum_{i=0}^{N-1} x(k-i). \quad (7)$$

- Low-pass filters remove high-frequency vibration while pre-serving the lower-frequency motion of braking, turning, falling and impact; moving-average or median filters reduce short-term variation in gas-sensor output; and temporal filtering rejects isolated false proximity detections by requiring a target to persist over several consecutive samples. Over-filtering can remove the very impact peaks the

system must detect, so filter strength must be tuned and not maximised.

2. Feature Extraction

Beyond the IMU features in Section IV, alcohol-sensor features include baseline voltage, moving average, maximum response, rise time, stability, standard deviation and persistence above a threshold. For blind-spot sensing, useful features are object presence duration, estimated distance, rate of change of distance, warning-zone occupancy and repeated-detection confidence. Peak detection can be done with standard routines such as MATLAB's findpeaks, which supports minimum peak height, prominence and spacing [13].

3. Threshold Optimisation and Decision Accuracy

Thresholds should be chosen from labelled data and not set arbitrarily. Experimental data can be labelled into classes such as stationary, normal riding, speed-breaker crossing, harsh braking, sharp turn, sudden movement, controlled impact, sensor fault and communication fault, and the feature distributions compared between classes. Candidate thresholds are then scored by

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \quad (8)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN}, \quad (9)$$

$$\text{Specificity} = \frac{TN}{TN + FP}, \quad (10)$$

where TP, TN, FP and FN are true positives, true negatives, false positives and false negatives.

4. Fault Detection and Diagnosis

Fault detection asks whether the measurement system works, whereas dynamics monitoring asks what the vehicle and rider are doing; a high reading may be a genuine event or a sensor malfunction. Model-based diagnosis compares a measured value $y(k)$ with an expected value $\hat{y}(k)$ and examines the residual [8],

$$r(k) = y(k) - \hat{y}(k), \quad |r(k)| > T \Rightarrow \text{possible fault}. \quad (11)$$

A residual above the threshold T signals an abnormal condition, but genuine events and faults must still

be separated by cross-checking sensors against each other. Faults fall into three categories.

- **Sensor faults:** range violations, excessive noise, and stuck-at faults in which the variance stays below a threshold ($\sigma^2 < T_{var}$) while another sensor shows motion.
- **Communication faults:** no valid packet arrives within a timeout window, $t_{current} - t_{last} > T_{timeout}$.
- **Data-consistency faults:** cross-sensor contradictions, for example the gyroscope shows movement while the accelerometer stays flat, are checked before a fault is confirmed.

5. Low variance on one sensor together with confirmed movement on another therefore indicates a possible stuck sensor, not a stationary vehicle.

5. Analysis Tools

Offline environments such as MATLAB can acquire data over serial or network links [14], apply filters [15], extract features and tune thresholds before simplified logic is deployed on an embedded controller such as the ESP32. This supports reproducible, quantitative evaluation of detection logic, but it is a tool and not a requirement of the approach.

VIII. PROPOSED FAULT-AWARE MULTISENSOR FRAMEWORK

Building on the gaps identified above, this section proposes a conceptual framework for a road-safety module that combines IMU-based event detection, MQ-3 alcohol-vapour screening and IR blind-spot sensing with fault-aware decision logic. The framework is a proposal derived from this review and has not yet been validated experimentally.

1. Architecture

Fig. 1 shows the proposed architecture. An embedded controller collects timestamped packets containing acceleration, angular velocity, alcohol-sensor output, proximity readings, communication status and battery status. The data then pass through four stages: validation (range, missing-data and time-out checks), filtering and feature extraction, cross-sensor consistency checking with fault

classification, and multi-condition event confirmation. The cross-checks extend beyond the IMU: MQ-3 readings are interpreted together with temperature, humidity and a warm-up flag, and IR detections are accepted only when they persist over several samples and are consistent with an ambient-light estimate.

2. Decision Logic

Every sample resolves to one of four states: Normal, Warning, Abnormal event or Sensor or communication fault. As Fig. 2 shows, invalid data (a range violation or missing packet) are routed directly to a fault state and valid data proceed to dynamics analysis. Features outside the normal-behaviour range raise a flag, and the flag is confirmed only if a second condition, such as angular velocity or a proximity reading, agrees. Confirmed events are reported as an abnormal event and unconfirmed ones as a warning, so that the rider or operator stays informed without relying on a single threshold crossing.

3. Proposed Validation Protocol

The framework should be validated through structured tests of increasing severity, with the expected state recorded before each test: (1) a stationary condition, expecting low variation, a Normal state and no false fault; (2) normal motion, expecting moderate changes and no false abnormal event; (3) a controlled sudden movement, expecting a temporary spike and a Warning or abnormal flag; (4) a controlled impact simulation, expecting a large acceleration peak and a confirmed Abnormal event; (5) sensor-fault injection with constant, out-of-range or missing values, expecting the matching sensor or data fault; and (6) communication interruption, expecting a timeout-triggered

communication fault. For the added sensors, MQ-3 readings should be compared with a calibrated reference instrument and IR range should be tested in sunlight, rain and darkness. Reported metrics should include accuracy, sensitivity, specificity, false-alarm rate, missed-detection rate and latency.

IX. COMPARATIVE ANALYSIS OF REPRESENTATIVE FILINGS

Table III compares three recent Indian patent applications, described by the road-safety functions they provide and not by their form factor. Patent documents state intended designs and do not report validated performance, so they show the direction of practice and not how well it works. A fourth filing [11] claims only a Bluetooth communication kit with solar charging and contains no safety sensing, so it is not tabulated. Three observations follow from these filings, and they describe these documents only and not the whole field. First, alcohol sensing with MQ-type sensors and crash alerting are common, whereas blind-spot or approaching-vehicle aware-ness appears in only one, and there it relies on cameras. Second, only one filing [12] describes self-testing or calibration of its own sensors, and none describes cross-sensor consistency checking. Third, none reports accuracy, datasets or field tests.

X. CHALLENGES AND RESEARCH GAPS

Despite progress, several technical and practical gaps remain.

Sensor drift and calibration instability are rarely addressed adequately. IMU bias, vibration-induced noise, changing sensor alignment, MQ-3 sensitivity variation and ageing can alter the reliability of thresholds over time.

MQ-3 reliability and legal admissibility. The MQ-3 is an SnO₂-based semiconductor sensor whose response depends on alcohol vapour but is also influenced by temperature, humidity, operating conditions, storage and other gases. MQ-3 systems should therefore be described as low-cost alcohol-vapour screening tools, not legally admissible breath-alcohol analysers. Future work should compare MQ-3 results with calibrated reference instruments and evaluate electrochemical fuel-cell sensors where greater selectivity and legal reliability are needed.

Limits of reflective IR in sunlight. Strong ambient light may saturate optical proximity measurements, and object colour, texture and reflectivity change the amount of reflected infrared light, so reflective IR sensors are of limited suitability for outdoor blind-spot monitoring.

Other important gaps include the following.

- Power and battery life: continuous sensing, wireless transmission, GPS, radar, buzzers and cloud connectivity increase energy use. Energy-

aware sampling, sleep modes, edge processing and battery-health monitoring need further study.

- User comfort and acceptance: alerts must be noticeable but not distracting. Frequent false alarms, bulky hardware, heat, poor mounting or uncomfortable wearable interfaces reduce adoption.

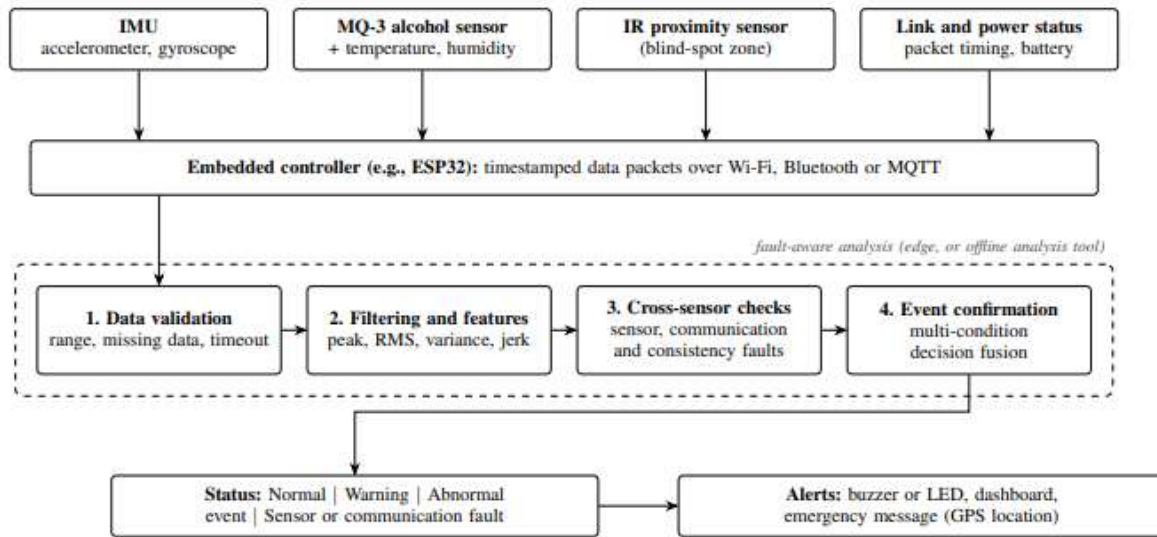


Fig. 1. Proposed fault-aware multisensor architecture. Data are validated and cross-checked before an event is confirmed, so that sensor malfunctions are not mistaken for rider events.

Table iii
Representative Patent Filings On Sensor-Based Rider Safety (Applications Examined In This Review)

Ref.	Filed	Road-safety functions	Sensors and links	Decision method	Reported validation	Fault awareness
[12]	Nov. 2025	Crash detection, injury-severity estimate, automatic emergency communication	Motion, impact, acoustic, barometric and biometric sensors (ECG, PPG, EEG); cellular and satellite links	On-board machine-learning classifier plus biometric severity index; adaptive thresholds	None reported	Power-up self-test, periodic calibration, sensor and power self-diagnostics, watchdog; no cross-sensor check described
[6]	Aug. 2025	Alcohol- and wear-based ignition interlock; crash detection with	MQ-series alcohol sensor; impact sensors (e.g., piezoelectric) at	Preset thresholds for alcohol and impact; ignition enabled only if worn and sober	None reported	None described

		emergency SMS	several points; wear switch; GPS; GSM; 433 MHz link to ignition			
[7]	Jun. 2021	Licence- and alcohol-based ignition control; approaching-vehicle alert; rear and blind-spot view	Iris sensor; MQ3 alcohol sensor; visor and rear cameras; tilt sensor; Hall speed sensor; speaker and vibration alert	Controller checks wear, licence and alcohol level before enabling ignition; alert intensity set by distance of approaching vehicle	None reported	None described

- Privacy: location, alcohol readings and riding behaviour are sensitive data, and consent, storage and sharing with third parties need clear policies.
- Lack of standardisation: studies use different sensor positions, acceleration thresholds, test methods, datasets and metrics, which makes direct comparison difficult.
- Lack of public datasets: most work relies on small private recordings or simulated impacts, and real crash data are scarce.
- Limited fault awareness: many prototypes detect a road event but do not verify whether the accelerometer, MQ-3, IR sensor, power supply or communication link is working correctly.

Future Directions

Future research should move beyond isolated accident detection toward an integrated, reliable and emergency-responsive safety ecosystem. A major direction is a fault-aware multisensor platform that combines IMU-based crash detection, alcohol-vapour screening, blind-spot monitoring, GPS tracking, communication monitoring and sensor-health assessment. Instead of alerting on a single threshold crossing, future systems should use confidence-based sensor fusion, in which acceleration, angular velocity, rider motion, proximity, GPS data and sensor reliability are evaluated together.

Blind-spot monitoring can be improved by replacing or

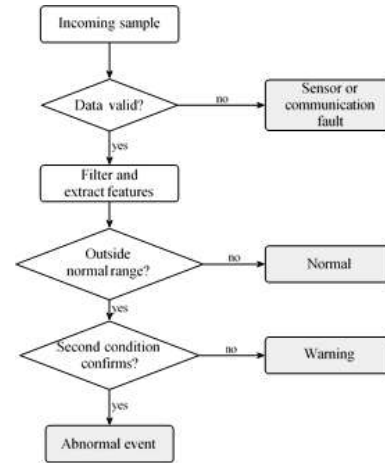


Fig. 2. Hierarchical decision logic. Each sample resolves to one of four states.

The proposed framework combines filtering, feature extrac-tion, threshold optimisation, sensor fusion and performance validation, and, most importantly, performs sensor and com-munication fault detection before a final safety decision is made. Such a fault-aware approach can distinguish genuine hazardous events from invalid measurements, improving reliability and reducing unnecessary alerts. Future work should validate the framework through controlled and real-road ex-periments, secure emergency communication, and integrate it with authorised healthcare and emergency-response networks.

CONCLUSION

This paper reviewed sensor-based IoT road-safety technolo-gies for powered two-wheelers, covering IMU-based crash and abnormal-motion detection, MQ-3 alcohol-vapour screen-ing, blind-spot monitoring, communication systems, signal processing and sensor-fault detection. Individual sensors can support useful safety functions, but no

single sensor performs dependably under all riding and environmental conditions.

IMUs can detect sudden impacts, abnormal rotation, falls, and post-event immobility, but single-threshold detection may trigger false alarms from potholes, speed breakers, harsh braking, and aggressive manoeuvres. MQ-3 sensors offer a low-cost approach to alcohol-vapour screening, but they need calibration, warm-up and environmental compensation and must not be treated as legally admissible breath-alcohol instruments. IR sensors can support short-range proximity warnings but are limited by sunlight, target reflectivity, weather and range; radar, ultrasonic sensing, cameras and fusion offer stronger long-term blind-spot solutions.

The proposed framework combines filtering, feature extraction, threshold optimisation, sensor fusion and performance validation, and, most importantly, performs sensor and communication fault detection before a final safety decision is made. Such a fault-aware approach can distinguish genuine hazardous events from invalid measurements, improving reliability and reducing unnecessary alerts. Future work should validate the framework through controlled and real-road experiments, secure emergency communication, and integrate it with authorised healthcare and emergency-response networks.

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REFERENCES

1. G. Savino et al., "Active safety systems for powered two-wheelers: A systematic review," *Traffic Inj. Prev.*, vol. 21, no. 1, pp. 78–86, 2020, doi: 10.1080/15389588.2019.1700408.
2. P. Lee et al., "Trends in smart helmets with multimodal sensing for health and safety: Scoping review," *JMIR mHealth uHealth*, vol. 10, no. 11, Art. no. e40797, 2022, doi: 10.2196/40797.
3. D. J. Warrington, E. J. Shortis, and P. J. Whittaker, "Are wearable devices effective for preventing and detecting falls: An umbrella review (a review of systematic reviews)," *BMC Public Health*, vol. 21, Art. no. 2091, 2021, doi: 10.1186/s12889-021-12169-7.
4. S. Subramaniam, A. I. Faisal, and M. J. Deen, "Wearable sensor systems for fall risk assessment: A review," *Front. Digit. Health*, vol. 4, Art. no. 921506, 2022, doi: 10.3389/fdgth.2022.921506.
5. M. Chen et al., "A systematic review of wearable sensor-based technologies for fall risk assessment in older adults," *Sensors*, vol. 22, no. 18, Art. no. 6752, 2022, doi: 10.3390/s22186752.
6. A. D. Ganer, R. S. Prajapati, V. D. Kurade, R. P. Kale, and R. G. Waghmare, "Smart helmet safety system for motorcyclists," *Indian Patent Appl.* 202521077254, Sep. 5, 2025.
7. N. Patil and H. Basavaraj, "Smart helmet for safety of rider," *Indian Patent Appl.* 202141025969, Jun. 25, 2021.
8. D. Li, Y. Wang, J. Wang, C. Wang, and Y. Duan, "Recent advances in sensor fault diagnosis: A review," *Sens. Actuators A, Phys.*, vol. 309, Art. no. 111990, 2020, doi: 10.1016/j.sna.2020.111990.
9. M. J. Page et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *BMJ*, vol. 372, Art. no. n71, 2021, doi: 10.1136/bmj.n71.
10. A. C. Tricco et al., "PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation," *Ann. Intern. Med.*, vol. 169, no. 7, pp. 467–473, 2018, doi: 10.7326/M18-0850.
11. K. Lenin et al., "Smart helmet inbuilt wireless communication kit and system," *Indian Patent Appl.* 202141028849, Jul. 9, 2021.
12. S. Kumawat, S. Saini, M. Patel, P. Jain, and Neetu, "Smart helmet with crash detection and alert system," *Indian Patent Appl.* 202511114979, Jan. 9, 2026.
13. MathWorks, "findpeaks: Find local maxima," *MATLAB Documentation*. [Online]. Available: <https://www.mathworks.com/help/signal/ref/findpeaks.html>. Accessed: Oct. 11, 2026.
14. MathWorks, "Serial and USB communication," *MATLAB Documentation*. [Online].

Available:

<https://www.mathworks.com/help/matlab/serial-port-devices.html>. Accessed: Oct. 11, 2026.

MathWorks, "lowpass: Lowpass-filter input signal," MATLAB Documentation. [Online]. Available:

<https://www.mathworks.com/help/signal/ref/lowpass.html>. Accessed: Oct. 11, 2026.