# An Affordable Six-Wheel Arduino Rover for Hands-On Learning in Planetary Robotics and Environmental Sensing with A Path Toward Edge AI

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doi.org/10.64643/ijirt.208523-459

***Abstract*—This work reviews recent literature (2021–2026) on low-cost rover platforms, educational robotics, six-wheel mobility, environmental sensing, and embedded machine learning, and positions an affordable six-wheel Arduino rover within this landscape. The platform pairs an Arduino Uno with six DC geared motors driven through an L298N dual H-bridge, while an HC-05 Bluetooth module links the chassis to an Android handset for basic teleoperation. A modular sensing bay can accommodate the DHT11 temperature-humidity sensor, the BMP280 barometric sensor, the HC-SR04 ultrasonic ranger, soil-moisture and light probes, MQ-series gas detectors, and the MPU6050 inertial unit. The chassis is designed in CAD for fabrication from acrylic sheet, keeping the projected build cost within a few thousand Indian rupees.**

**The review synthesises peer-reviewed literature indexed in major scholarly databases, supplemented by an authenticated NASA technical memorandum, spanning flight autonomy on Perseverance, deep-learning terrain classification, rocker-bogie suspension optimisation, low-cost sensor calibration, and meta-analytic findings on robotics-supported learning.**

**Five recurring management concerns emerge: purpose, hardware, sensing, process, and reliability. We organise these into a development framework for student-built rovers and map a staged upgrade path toward future TinyML inference, autonomous obstacle avoidance, GPS-assisted navigation, and IoT telemetry. AI is therefore positioned as a future capability rather than a demonstrated onboard function, with the present design providing the sensing, control, and data-acquisition foundation for subsequent TinyML deployment. The platform is an educational terrestrial rover, not flight-qualified planetary hardware. The literature supports hands-on robotics as a means of developing computational thinking and STEM engagement, while the proposed platform provides a practical setting for such learning.**

***Index Terms*—Artificial Intelligence; Arduino Uno; Six-Wheel Rover; Planetary Robotics; Environmental Sensing; Bluetooth Control; Embedded Systems; Educational Robotics; TinyML**

## I. INTRODUCTION

Autonomy now drives real science on Mars. During its first two years of surface operations, the Perseverance rover let its on-board AutoNav system plan and execute drives that ground controllers never scripted, covering record single-sol distances through hazard-rich terrain [1]. The same vehicle carries the Mars Environmental Dynamics Analyzer, a coordinated suite of pressure, temperature, humidity, wind, and radiation sensors that samples the Martian boundary layer around the clock [2]. These two capabilities, autonomous mobility and distributed environmental sensing, define what a modern planetary rover actually does.

Cost remains a major barrier. Mission-class hardware sits far beyond any teaching laboratory, and even research-grade rover testbeds strain departmental budgets. Recent work has begun to address this barrier. Mahmood and Baluch demonstrated a low-cost planetary-rover analogue that fuses multiple cheap sensors in real time on embedded hardware for obstacle-aware navigation [3], and NASA's own Open-Source Rover has been extended into an autonomous research platform built from commodity parts [4]. In parallel, open-hardware journals now publish peer-reviewed educational robot designs, including differential-drive kits built specifically so that students can replicate, modify, and extend them [5], [6].

Education research supplies the second motivation. Systematic reviews and meta-analyses published since 2021 converge on a consistent finding: physical robot construction improves computational thinking, strengthens STEM attitudes, and yields measurable learning gains across age groups [7]–[10]. Arduino occupies a central place in this evidence base because its toolchain lowers the entry barrier for programming, electronics, and mechanical integration at once [11], [12].

Two requirements follow. First, students need a platform they can afford, assemble, break, and repair, one that exercises motor control, wireless communication, sensor interfacing, and embedded programming in a single project rather than as isolated laboratory exercises. Second, that platform must leave a growth path open: toward on-board machine-learning inference, autonomous obstacle avoidance, and networked telemetry, so that a first-year teleoperated build can become a final-year autonomy project without a redesign. The proposed six-wheel Arduino rover is designed to address both requirements. It combines an Arduino Uno, six DC geared motors, an L298N motor driver, and an HC-05 Bluetooth module on an acrylic chassis, with a modular bay for environmental and inertial sensors.

This paper is a literature review with a proposed rover design. Section 2 reviews recent peer-reviewed work across five streams: planetary rover autonomy, low-cost and open-hardware rover platforms, educational robotics outcomes, six-wheel mobility mechanics, and environmental sensing with embedded intelligence. Section 3 describes the proposed system architecture. Section 4 sets out the integration challenges that a student-built rover must manage. Section 5 proposes a five-principal development framework. Section 6 discusses advantages, limitations, and open problems. Section 7 charts future enhancements, and Section 8 concludes.

## II. LITERATURE REVIEW

### 2.1. Research Methodology

This study follows a qualitative, narrative-synthesis design. We searched Scopus- and Web of Science-indexed journals for work published between 2021 and 2026, restricting selection to peer-reviewed articles from publishers including Elsevier, Springer Nature, Wiley, IEEE, SAGE, and Cambridge University Press, with strong preference for Q1 and Q2 outlets. Search themes covered planetary rover autonomy, low-cost rover platforms, Arduino-based educational robotics, rocker-bogie and six-wheel suspension design, terrain classification with deep learning, low-cost environmental sensor calibration, and machine learning on microcontroller-class hardware. Government sources were limited to authenticated NASA technical records [4]. Sources entered the review only when their bibliographic details, including DOI, could be verified against the publisher record. Studies were compared on mobility mechanism, controller platform, communication method, sensing payload, autonomy level, cost class, and educational evidence. No primary data collection took place; the proposed design description in Section 3 reports design characteristics rather than controlled experimental benchmarks, and Section 6.3 states this limitation plainly.

### 2.2. Autonomy on Flight Rovers: The Current Ceiling

Perseverance sets the reference point. Verma and colleagues report that the rover's self-driving system processed stereo imagery on a dedicated compute element, built local hazard maps, and selected arcs fast enough to drive while thinking, a first for Mars surface operations [1]. The result was not a stunt. Autonomous drives let the vehicle reach science targets weeks earlier than ground-in-the-loop planning would allow. Environmental sensing advanced in step: MEDA delivers a synchronised, multi-point record of pressure, air and ground temperature, relative humidity, wind, dust opacity, and radiation, turning the rover into a mobile weather station [2].

Perception research pushes the ceiling higher. Deep networks now classify Martian terrain from orbital and rover imagery for landing-site assessment and traverse planning [13], [14]. Semantic segmentation models tuned for Martian scenes, including hybrid-attention and dual-branch architectures, feed traversability estimates directly into path planners [15], [16]. Terrain classification from Zhurong rover images extends the evidence beyond NASA missions [17]. Proprioceptive learning matters too: Ugenti and colleagues show that signal and feature selection strongly conditions how well a planetary robot learns terrain from its own vibration and current signatures [18]. Path-planning research has begun to formalise the operational metrics that human rover drivers actually care about [19], while probabilistic traversability models with test-time adaptation quantify their own uncertainty before committing a rover to soft ground [20]. Multi-modal feature learning now supports terrain-relative navigation estimates as well [21]. These deep-learning workloads are beyond the practical capability of an eight-bit microcontroller such as the Arduino Uno. All of it defines the conceptual destination toward which an educational platform should point.

### 2.3 Low-Cost and Open-Hardware Rover Platforms

A parallel research stream asks how much rover capability can be retained at substantially lower cost. Mahmood and Baluch answer: quite a lot. Their embedded multi-sensor fusion pipeline achieves robust obstacle-aware navigation on hardware costing a small fraction of research-grade testbeds [3]. NASA's Open-Source Rover, a six-wheel rocker-bogie replica built from commercial parts, has been upgraded into a full autonomous research platform, demonstrating that the commodity route scales beyond teleoperation [4].

Open-hardware journals give this stream its reproducibility. Betancur-Vasquez and colleagues published a complete open-source, open-hardware mobile robot for education and research, with every design file released for replication [5]. Pantos and colleagues went further with ReFiBot, an educational robotic kit designed around circularity and open science, assembled from inexpensive components and programmed through a beginner-friendly Arduino environment [6]. Both papers emphasise reproducibility because their designs can be rebuilt and audited. The proposed six-wheel rover follows this ethos: commodity parts, documented wiring, and a chassis any college workshop can cut.

### 2.4 Educational Robotics: What the Evidence Says

Does building robots actually teach anything? The quantitative record says yes. Zhang and colleagues' systematic review found that educational robots improved computational thinking and STEM attitudes across K-12 studies [7]. Wang and colleagues' meta-analysis of controlled studies estimated a significant positive effect of educational robots on learning outcomes overall [8]. Darmawansah and colleagues mapped the robotics-based STEM literature and found engagement and problem-solving among the most consistently reported gains [9]. Ching and Hsu reached parallel conclusions for computational-thinking development in younger learners [10].

Arduino anchors the university-level evidence. Wang, Coutras, and Zhu embedded Arduino-based robot construction in a situated-learning course design and reported improved robotics proficiency among computing students [11]. Marin-Marin and colleagues' systematic review of Arduino in education catalogued its use across programming, electronics, and simulated rover missions [12]. Eye-tracking work on Tinkercad-based Arduino instruction adds usability evidence for the simulation-first pathway that many student teams follow before committing to hardware [22]. Taken together, the education stream justifies the pedagogical premise of this project: a hands-on rover build is not a gimmick but an evidence-backed instructional strategy.

### 2.5 Six-Wheel Mobility and Suspension Mechanics

Why six wheels? The mechanics literature answers with load distribution and obstacle negotiation. Li and colleagues optimised rocker-bogie suspension dimensions against kinetostatic and terramechanic criteria, showing how link geometry governs wheel-load uniformity on irregular ground [23]. Cosenza and colleagues analysed a modified rocker-bogie theoretically and mapped the conditions under which it climbs steps that defeat four-wheel layouts [24]. An and Kang introduced a glass-fibre beam-spring rocker-arm suspension for six-wheeled robots, cutting part count while preserving terrain compliance [25]. Rajath and colleagues' review consolidates a decade of rocker-bogie design, manufacturing, and control progress into a single reference [26].

The educational implication is direct. A rigid six-wheel chassis with three motors per side, as specified for the proposed rover, captures the load-sharing benefit of six contact points without the machining burden of a full rocker-bogie linkage. Students first experience skid-steer control on the rigid frame. The literature then hands them a documented upgrade path, from beam-spring arms to full rocker-bogie, when their projects demand true obstacle climbing [23]–[26].

### 2.6 Environmental Sensing, Calibration, and Data Quality

Low-cost sensors can exhibit significant systematic errors. That blunt fact organises the recent calibration literature. Liang's review of low-cost ambient-air sensor calibration catalogues drift, cross-sensitivity, and humidity interference as systematic error sources, and surveys the regression and machine-learning corrections that tame them [27]. Tancev and de Toro applied variational Bayesian methods to calibrate low-cost gas sensor systems against reference stations [28]. On the systems side, Moursi and colleagues built an IoT architecture that performs air-quality prediction at the network edge [29], and Buelvas and colleagues' systematic mapping study frames data quality as the central open problem in IoT air-quality monitoring [30].

For a student rover carrying DHT11, BMP280, and MQ-series sensors, these findings convert directly into curriculum. Raw MQ-135 voltage is not a gas concentration. Students who log rover sensor data against a reference instrument, fit a correction, and quantify residual error are practising exactly the workflow the calibration literature prescribes [27], [28]. The sensing payload therefore serves double duty: it makes the rover scientifically useful and it teaches measurement honesty.

### 2.7 Embedded Intelligence: TinyML and the Path to On-Board AI

Machine learning no longer requires a server. Saha, Sandha, and Srivastava's review of machine learning for microcontroller-class hardware documents quantised networks, pruning, and specialised inference runtimes that squeeze useful models into kilobytes of RAM [31]. This matters for the upgrade path: an Arduino Uno cannot run a vision model, but a low-cost co-processor can host keyword spotting, vibration-based terrain classification, or gas-signature recognition. The proprioceptive terrain-learning results from planetary robotics [18] scale down naturally, since accelerometer and motor-current features of the kind an MPU6050 provides are exactly what those classifiers consume.

### 2.8 Cross-Domain Applications of Low-Cost Ground Robots

Rover skills transfer. Agricultural robotics reviews document autonomous ground platforms for field scouting, with perception systems and mobility requirements that mirror planetary analogues at friendlier stakes [32]–[34]. Response and rescue robotics surveys trace the same sense-move-report loop into disaster settings [35], and the ethics literature around rescue robots reminds designers that deployment context shapes responsibility [36]. A student who masters the six-wheel Arduino platform is therefore acquiring competencies with documented demand across agriculture, inspection, and emergency response, not merely space enthusiasm.

### 2.9 Research Gaps Identified

Five gaps emerge from this synthesis. First, most published educational robots are two- or three-wheel differential platforms [5], [6]; peer-reviewed six-wheel educational designs remain scarce even though the mechanics literature explains their advantages [23]– [26]. Second, educational platforms rarely integrate environmental sensing with the calibration discipline the sensing literature demands [27], [30]. Third, the TinyML pathway from teleoperation to on-board inference is well documented in the embedded-ML literature [31] but almost never packaged into a staged student curriculum. Fourth, low-cost rover papers report design and navigation performance [3], [4] but seldom measure educational outcomes, while education papers measure learning [7]– [10] on platforms with little scientific payload. Fifth, cost reporting is inconsistent across the literature, which frustrates replication in budget-constrained institutions. The proposed rover responds to the first three gaps through its design and provides a platform for investigating the fourth and fifth gaps.

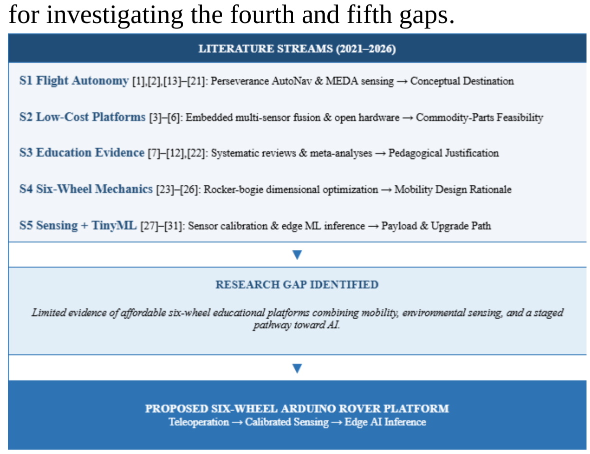
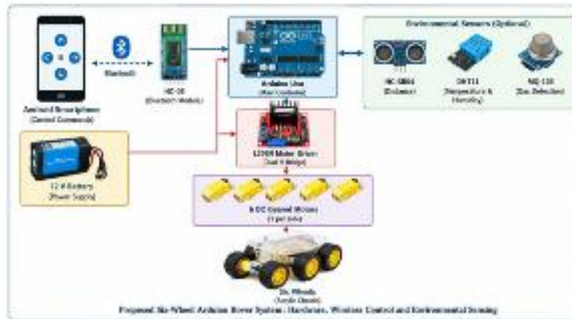



*Fig. 1. Literature-to-system flow: how the five review streams converge on the proposed platform. Original diagram.*

## III. PROPOSED SIX-WHEEL ARDUINO ROVER SYSTEM

### 3.1 System Architecture

The rover is deliberately simple. An Arduino Uno serves as the central controller, receiving commands through the HC-05 Bluetooth serial link, controlling the L298N dual H-bridge, and polling the sensors installed for each experiment. The L298N provides two H-bridge channels, with three DC geared motors connected in parallel on each channel to drive the left and right wheel groups; because the motors' rated and stall currents were not experimentally characterised in this study, the combined current and thermal load should be verified against the driver's limits before sustained operation. The proposed architecture separates the motor and logic power paths, with regulation and decoupling intended to reduce motor-induced supply disturbances. The CAD-designed acrylic chassis incorporates a modular sensor bay, allowing different sensing payloads to be added or replaced without rewiring the drive system. Figure 2 presents the overall block architecture. The L298N was selected because of its low cost and suitability for introductory motor-control education; however, its voltage drops and current limitations should be considered when selecting motors or operating under sustained loads. For higher-current motors or demanding operating conditions, a higher-efficiency MOSFET-based motor driver is recommended.



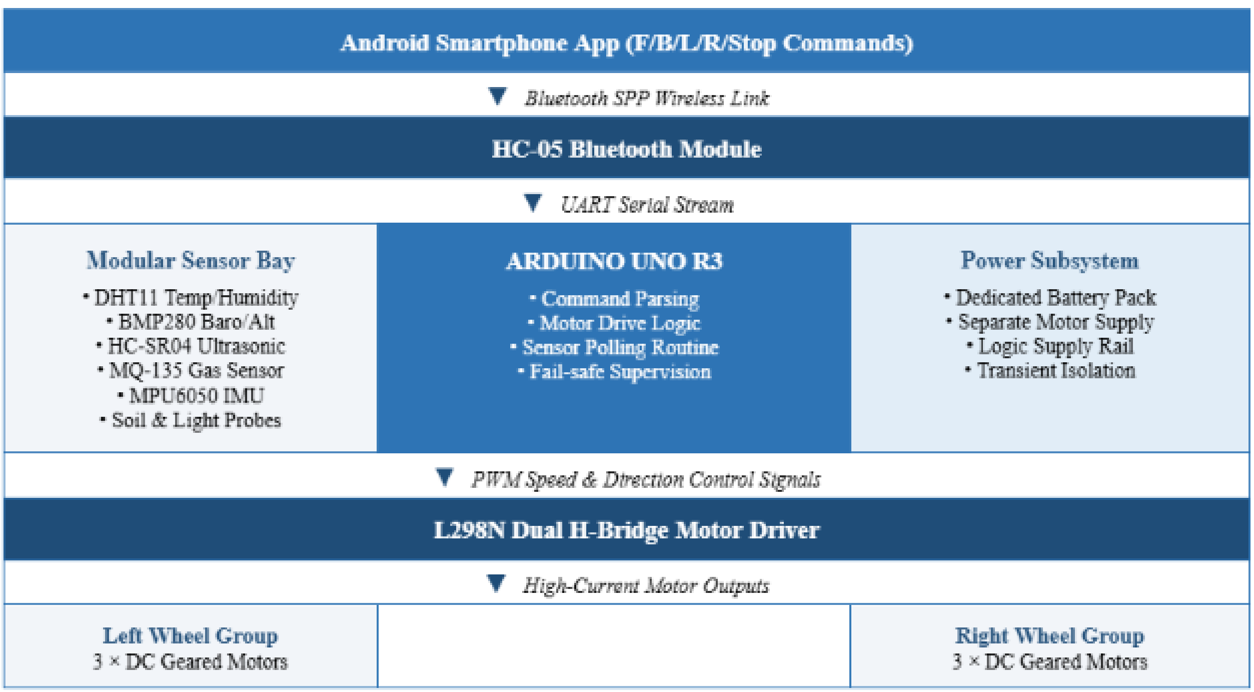



*Fig. 2. System architecture and representative sensing configuration of the proposed rover.*

### 3.2. Six-Wheel Mobility and Motor Control

Skid steering provides a mechanically simple control configuration. The left and right motor groups run as two channels; equal drive moves the rover straight, differential drive turns it, and opposed drive spins it in place. Six contact points distribute vehicle load across the wheels and can improve load sharing compared with simpler two-wheel educational platforms, consistent with the load-distribution findings reported in the suspension literature [23], [26].

The L298N provides the motor-switching interface between the Arduino control signals and the motor groups, subject to its voltage, current, and thermal limits.

3.3 Wireless Control

The HC-05 can communicate with compatible Android devices using Bluetooth Classic Serial Port Profile (SPP). Single-character commands select forward, reverse, left, right, and stop. The scheme is trivial by design: a first-year student can trace every byte from touchscreen to wheel. That traceability is the pedagogical point, and it mirrors the replicability values of the open-hardware platforms reviewed in Section 2.3 [5], [6].

3.4 Sensing Payload

Table 1 summarises the proposed sensor payload and its intended measurement classes, mission analogues, and calibration considerations. Each sensor maps to a measurement class, a rover-mission analogue, and the calibration caution the literature attaches to it.

*Table 1. Sensing payload and mission analogues.*

| Sensor | Measures | Mission Analogue | Calibration Caution |
| --- | --- | --- | --- |
| DHT11 | Air temperature, relative humidity | MEDA air-temperature & humidity channels [2] | Coarse resolution; slow response; log against reference [27] |
| BMP280 | Barometric pressure; derived relative altitude | MEDA pressure sensing [2] | Thermal drift; requires warm-up window |
| HC-SR04 | Ultrasonic range (2–400 cm) | Hazard proximity for obstacle avoidance [3] | Beam spread; soft targets under-read |
| Soil-Moisture Probe | Relative soil-moisture indicator | Regolith moisture proxy; agricultural scouting [32] | Electrode corrosion; relative values only |
| Light / Colour Sensors | Illuminance, surface color | Surface classification cues [13] | Ambient-light coupling |
| MQ-135 Gas Sensor | Air quality / gas response | Gas-response / air-quality indicator [27], [28] | Gas response is humidity-sensitive; calibration advised [27], [28] |
| MPU6050 IMU | 3-axis acceleration & gyroscope | Proprioceptive terrain sensing [18] | Bias drift; filtering and sensor fusion recommended |

3.5 Bill of Materials and Cost Class

Affordability is a design requirement, not an accident. Table 2 lists the core build with indicative Indian retail cost classes. The listed component set has an indicative cost of approximately INR 2,900–5,800. This places the proposed platform in a substantially lower cost class than many research-oriented rover platforms and is consistent with the affordability ethos of open-hardware educational robotics [5], [6].

*Table 2. Core bill of materials (indicative cost classes).*

| Component | Qty | Role | Indicative Cost Class (INR) |
| --- | --- | --- | --- |
| Arduino Uno R3 | 1 | Central controller | 400–800 |
| DC Geared Motor + Wheel | 6 | Traction & propulsion | 600–1,200 (set) |
| L298N Dual H-Bridge Driver | 1 | Motor power drive stage | 150–250 |
| HC-05 Bluetooth Module | 1 | Wireless communications | 250–350 |
| Acrylic Chassis (CAD-cut) | 1 | Structural chassis | 300–600 |
| Battery Pack + Holder | 1 | Motor & logic power rails | 300–700 |
| Sensor Suite (Table 1) | 1 | Environmental payload | 700–1,500 |
| Wiring, Fasteners, Misc. | — | Hardware integration | 200–400 |

3.6 Staged Development Path

The platform is designed as a staged development pathway rather than a fixed end-state. Stage one establishes Bluetooth teleoperation and basic motor control. Stage two adds the sensing payload with logged, calibrated data. Stage three introduces reactive autonomy: ultrasonic obstacle stops and simple avoidance turns. Stage four attaches a microcontroller-class ML co-processor for on-board inference over inertial and gas-sensor features, following the TinyML methods reviewed by Saha and colleagues [31]. The AI stage is proposed as a future extension; no machine-learning model is trained or evaluated on the present rover. Each stage can be structured as a semester-scale student project with a defined deliverable.

## IV. INTEGRATION CHALLENGES FOR A STUDENT-BUILT ROVER

The literature and the proposed system architecture identify several integration challenges that student rover projects must address. Power comes first. Six motors under load brown-out a shared supply and reset the controller; separating motor and logic rails, as the architecture in Figure 2 does, reduces the most common failure mode. Mechanical alignment comes second: asymmetric motor mounting can produce curved trajectories during nominal straight-line motion, providing a practical lesson in mechanical tolerances.

Sensing raises subtler problems. Every sensor in Table 1 carries a calibration caveat, and the air-quality literature is emphatic that uncorrected low-cost gas readings mislead [27], [28], [30]. Communication reliability matters too: dropped Bluetooth bytes must fail safe into a stop state, a small lesson in defensive embedded design. Software ties these threads together. The control loop must service the serial port, the motor logic, and the sensor polls without blocking; students meet cooperative scheduling long before an operating-systems course names it. Finally, autonomy must wait its turn. The staged path in Section 3.6 exists because bolting navigation onto an unproven drive base compounds errors, a sequencing discipline the flight literature models at much larger scale [1].

## V. A FIVE-PRINCIPAL DEVELOPMENT FRAMEWORK

Section 4's challenges repeat across every low-cost rover project the review surfaced. We organise their management into five interdependent principles: Purpose, Hardware, Sensing, Process, and Reliability. The framework guides student teams and supervising faculty; it does not pretend to govern flight programmes. Table 3 states each principle, its core concern, and its concrete application on this platform.

*Table 3. The five principles of the proposed development framework.*

| Principle | Core Concern | Application on Proposed Rover |
|---|---|---|
| Purpose | Every component earns its place through a stated learning or measurement objective. | Each sensor in Table 1 maps to a mission analogue and a named skill outcome, consistent with evidence-backed robotics pedagogy [7]– [10]. |
| Hardware | Controller, drive stage, power, and structure must match mobility requirements and budget. | Uno + L298N + six geared motors on split power rails; acrylic chassis cut from CAD drawings (Table 2). |
| Sensing | Sensors are selected for required information and rigorously calibrated, not merely connected. | Reference-logging and correction workflow drawn directly from low-cost calibration literature [27], [28]. |
| Process | Development is staged, with each capability checked before adding the next level of complexity. | Four-stage ladder: teleoperation, calibrated sensing, reactive autonomy, and edge-ML inference (Section 3.6) [31]. |
| Reliability | Fail-safe defaults, stable power, and active supervision keep the platform safe and repeatable. | Stop-on-link-loss behavior; separated power supplies; active supervision during autonomy trials. |

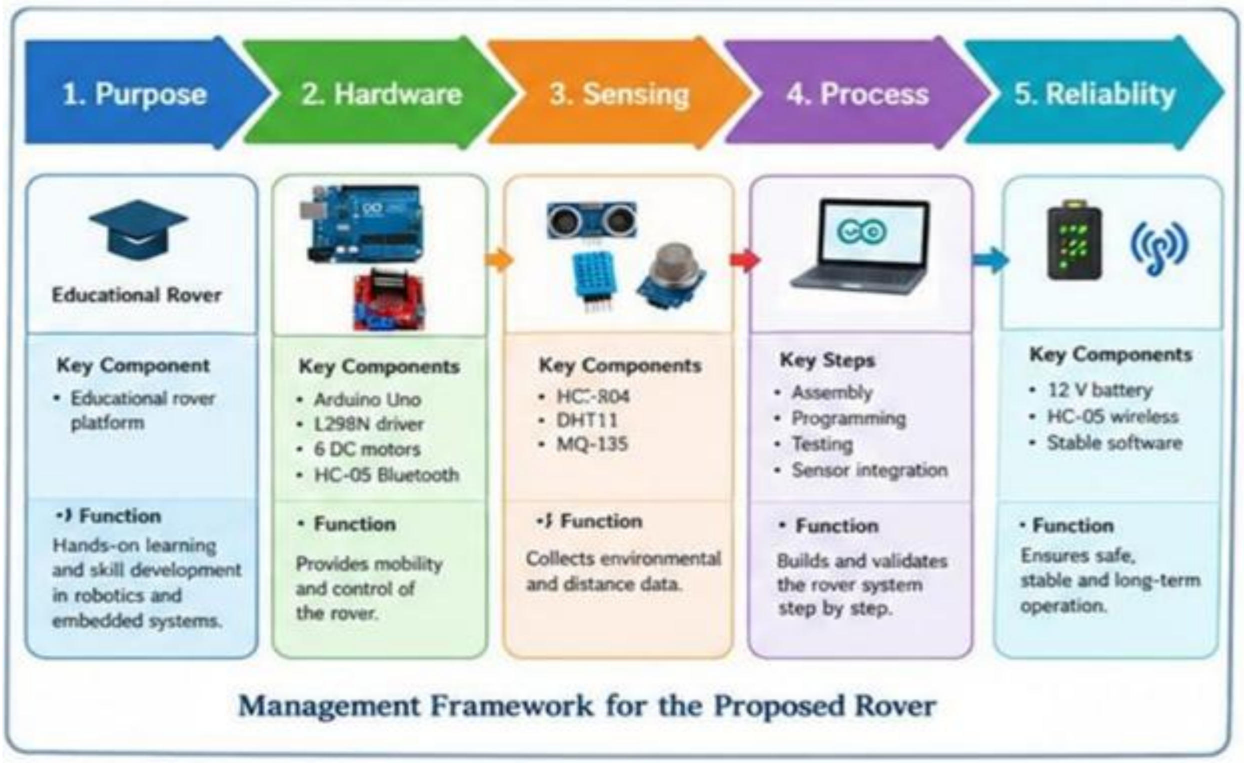



*Fig. 3. Management framework diagram for the proposed rover.*

Purpose reflects the outcome-measurement discipline of the education stream [7]– [10]. Sensing encodes the calibration warnings of the air-quality stream [27], [30]. Process mirrors the staged-capability discipline that flight autonomy itself followed [1]. Reliability restates the fail-safe conventions of field robotics across agriculture and rescue domains [32], [35].

## VI. DISCUSSION

### 6.1 Comparative Positioning

Table 4 positions the proposed rover against representative platform classes from the review. The comparison clarifies what the platform is and is not.

*Table 4. Platform class comparison.*

| Attribute | Flight Rover [1],[2] | Research Rover [3],[4] | Edu-Robot [5],[6] | Proposed Rover |
|---|---|---|---|---|
| Cost Class | Mission-scale | USD Hundreds–Thousands | USD Tens–Hundreds | INR Few Thousand |
| Mobility Mechanism | 6-wheel rocker-bogie | 4–6 wheels, varied | 2–3-wheel differential | 6-wheel rigid skid-steer |
| Autonomy Level | On-board AutoNav planning | Embedded fusion navigation | Teleop / line-following | Teleop → Staged edge AI |
| Sensing Payload | MEDA multi-sensor suite | Task-specific sensors | Minimal | Seven-sensor modular payload |
| Primary Objective | Planetary science | Navigation research | Teaching basics | Pedagogy + Calibrated AI |
| Replicability | Mission-specific / restricted | Partial | Full (open hardware) | Full (commodity CAD) |

### 6.2 Advantages of the Proposed Platform

Five advantages follow from the synthesis. The low indicative cost may support individual or small-team student access, consistent with the broader emphasis on accessible hands-on robotics in the education literature [7], [9]. The six-wheel layout gives students genuine contact with the mobility class that planetary missions use, at a mechanical complexity they can actually build [23], [26].

The modular payload turns one chassis into many experiments, from soil scouting [32] to air-quality transects [29]. The staged ladder embeds a documented route to embedded AI [31] rather than a vague promise. The design is intended to support auditing, rebuilding, and iterative improvement, consistent with the open-hardware principles demonstrated by the reviewed platforms [5], [6].

### 6.3 Limitations

Honesty about scope protects the contribution. This is a terrestrial teaching instrument; nothing here is flight-qualified. The rigid chassis forgoes true rocker-bogie articulation, so step-climbing performance will trail the optimised suspensions in the mechanics literature [23]– [25]. Bluetooth range confines operations to classroom scale. Sensor readings remain indicative until each unit passes the calibration workflow of Section 5, and the MQ-series caveats are strict [27], [28]. Most importantly, this paper reports a literature synthesis and a positioned design: controlled measurements of learning outcomes on this specific platform, and quantitative benchmarks for speed, range, endurance, and obstacle detection, remain future work. The review also inherits the limits of narrative synthesis; a registered systematic protocol would strengthen a successor study.

### 6.4 Measurable Impact Parameters

Future evaluation should quantify, at minimum: total build cost against the Table 2 envelope; straight-line deviation over a fixed distance as a drive-symmetry metric; Bluetooth command latency and effective range; battery endurance under a standard drive cycle; per-sensor error after calibration against references; obstacle-detection distance and false-stop rate in stage three; and pre/post computational-thinking scores using the validated instruments of the education literature [7], [8]. Publishing these numbers would directly address the fourth and fifth research gaps identified in Section 2.9.

## VII. FUTURE ENHANCEMENTS AND PROPOSALS

The upgrade agenda follows the ladder. Near term: replace blocking sensor reads with a millis()-based scheduler; add wheel encoders for closed-loop speed; and log all telemetry to SD for post-run analysis. Middle term: mount a TinyML-capable co-processor and train a vibration-based terrain classifier from MPU6050 features, transplanting the proprioceptive methods of planetary terrain learning [18] onto microcontroller hardware [31]; add GPS for outdoor waypoint runs; and swap Bluetooth for a long-range IoT link so the rover reports environmental data to a dashboard in the pattern of edge air-quality systems [29]. Longer term: introduce a camera with off-board semantic segmentation inspired by the Mars terrain-perception literature [15], [16]; prototype a beam-spring or rocker-bogie suspension retrofit following the published mechanics [23], [25]; and attach a simple manipulator for simulated sample collection. As a research proposal, we suggest a multi-institution study that distributes identical rover kits, applies the Section 6.4 metrics, and measures learning outcomes with controlled designs, closing the platform-evidence gap this review exposed.

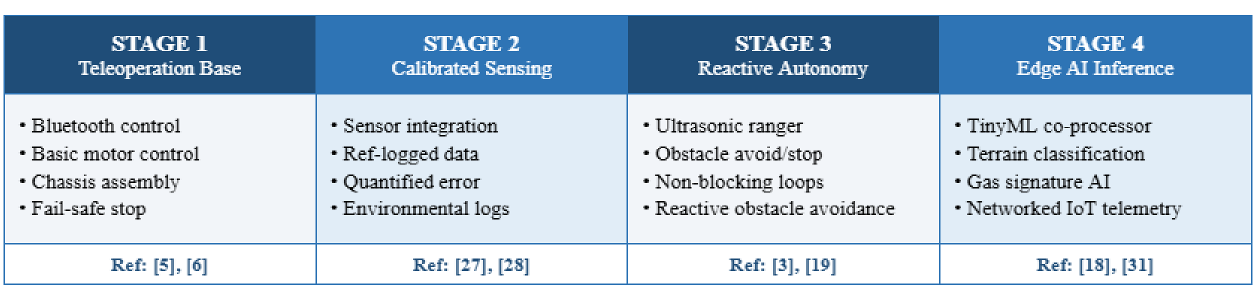



*Fig. 4. Staged upgrade roadmap. Original diagram.*

## VIII. CONCLUSION

Planetary rover technology has achieved increasingly sophisticated levels of autonomy and sensing, while comparable capabilities remain difficult to reproduce in typical educational laboratories. This review traced five literature streams from 2021 to 2026, spanning flight autonomy, low-cost platforms, education evidence, six-wheel mechanics, and calibrated sensing with embedded intelligence, and identified a clear gap: our narrative synthesis found limited evidence of educational six-wheel platforms that integrate environmental sensing with a staged pathway toward embedded AI. The proposed Arduino rover addresses this gap at the design level through an affordable and transparent component architecture that integrates six-wheel mobility, modular sensing, and a staged pathway toward embedded AI. The embedded-AI component is therefore a planned extension, while the present contribution is the affordable rover architecture, calibrated sensing framework, and staged educational pathway that enable its future implementation. Its architecture is deliberately transparent, its payload maps sensor functions onto corresponding mission-level measurement analogues, and its five-principal framework—Purpose, Hardware, Sensing, Process, and Reliability—translates findings from the reviewed literature into a practical structure for student rover development. The proposed platform provides students with hands-on exposure to the core concepts underlying planetary rover autonomy, sensing, and embedded intelligence. The next step is measurement: build the kits, run the metrics, and publish the numbers.

## ACKNOWLEDGEMENTS

The authors thank the Prof. Dr. V. B Kadam, Principal, the Head of the Department, and the teaching and non-teaching staff of the Department of Electronic Science, MVP's K.K.W. Arts, Science and Commerce College, Pimpalgaon Baswant, Nashik, for facilities, guidance, and support.

## DECLARATIONS

Funding: This work received no external funding. Conflicts of interest: The authors declare none. Data availability: Component specifications and technical details derive from the sources cited in the manuscript.

AI Declaration

The authors acknowledge the use of AI-assisted tools for language refinement, structuring, and revision support during manuscript preparation. The project concept, system design, technical content, analysis, and conclusions are the authors' own. The authors reviewed and edited the manuscript and accept full responsibility for the final content.

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APPENDIX A.

Study Design and Scope of Key Reviewed Sources

*Table A1. Methodological profile of principal sources (2021–2026).*

| Ref | Design | Domain | Contribution to Review |
|---|---|---|---|
| [1] | Flight operations report | Mars surface autonomy | Defines the autonomy ceiling and staged-capability discipline |
| [2] | Instrument description | Planetary environmental sensing | Mission analogue for the sensing payload (Table 1) |
| [3] | Embedded systems experiment | Low-cost rover navigation | Feasibility of obstacle-aware navigation on cheap hardware |
| [4] | NASA technical memorandum | Open-source rover autonomy | Commodity-parts route scales beyond teleoperation |
| [5], [6] | Open-hardware design articles | Educational robot kits | Replicability standard the proposed platform follows |
| [7]–[10] | Systematic reviews / meta-analysis | Educational robotics outcomes | Quantified learning-gain evidence |
| [11], [12], [22] | Course study / reviews / eye-tracking | Arduino pedagogy | University-level Arduino teaching evidence |

| Ref | Design | Domain | Contribution to Review |
|---|---|---|---|
| [13]–[17] | Deep-learning model studies | Mars terrain perception | Conceptual destination for camera-stage upgrades |
| [18]–[21] | Field robotics / planning studies | Terrain learning and planning | Proprioceptive methods portable to TinyML stage |
| [23]–[26] | Mechanics analyses / review | Rocker-bogie suspension | Design rationale for six-wheel mobility |
| [27]–[30] | Calibration and IoT studies | Low-cost sensing quality | Calibration workflow embedded in framework |
| [31] | Technical review | TinyML on microcontrollers | Feasibility of stage-four edge inference |
| [32]–[36] | Domain reviews | Agriculture, rescue robotics | Cross-domain transfer of rover competencies |