

# Development of an IoT-Based Prototype for Optimizing Hazardous Materials and Equipment Storage to Enhance HSE in Laboratories

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**Silviana Windasari**

Department of Electrical Engineering, Faculty of Engineering, Universitas Sains Indonesia, Bekasi, Indonesia

**Abdurohman**

Department of Electrical Engineering, School of Bioscience, Technology and Innovation (SBTI), Atma Jaya Catholic University of Indonesia, Jakarta, Indonesia

**Imbuh Rochmad**

Professional Engineer Program, Faculty of Engineering, Universitas Mercu Buana, Jakarta, Indonesia

**Setiyo Budiyanto**

Department of Electrical Engineering, Faculty of Engineering, Universitas Mercu Buana, Jakarta, Indonesia

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**Abstract:** Laboratory incidents are often precipitated by misplacement of hazardous materials and delayed recognition of unsafe conditions. Earlier laboratory safety solutions typically centered on sensors and dashboards, including IoT monitoring, improve situational awareness but remain largely reactive, operate at room/building scale, seldom enforce item-level storage rules, and rarely report alert selectivity (false-alarm behaviour). This work presents a compact prototype that combines RFID-based storage-zone verification with environmental sensing to support Health, Safety, Security, and Environment (HSSE) compliance at the storage-unit level. An ESP32-based controller integrates three RFID readers (low/medium/high-risk compartments) with temperature humidity and gas sensors; data are streamed to an IoT interface for real-time visualization and notification (e.g., implemented via Blynk), while rule-based logic triggers local (buzzer) and remote alerts when a tagged item is placed in the wrong zone or thresholds are exceeded. A scenario-driven evaluation across 18 cases (correct/mismatched placements for representative items) yielded 100% RFID tag detection and placement validation, an average response time of 2.37 s, and no false alarms under correct placements. These results indicate that joining placement verification with multi-sensor monitoring provides selective, low-latency warnings while avoiding nuisance alerts, establishing quantitative baselines for scalable smart-laboratory HSSE enforcement.

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Correspondents Author:

Abdurohman, Department of Electrical Engineering, School of Bioscience, Technology and Innovation (SBTI), Atma Jaya Catholic University of Indonesia, Jakarta, Indonesia

Email: kang.abdurohman@gmail.com

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## Introduction

Laboratory incidents frequently arise from misplacement of hazardous materials and delayed recognition of unsafe conditions. In electrical engineering and chemistry teaching labs, risks span corrosive chemicals, high-energy batteries, and thermal or electrical hazards that can quickly escalate if not addressed. Therefore, effective Health, Safety, Security, and Environment (HSSE) practice requires not only hazard detection but also preemptive enforcement of storage rules at the source of the risk. Consistent with ISO 45001:2018, occupational health and safety management should integrate hazard identification, risk assessment, and operational controls; however, these standards are rarely implemented at the item level in university laboratories. Conventional controls like manual inventories, signage, and periodic inspections raise awareness but are reactive and prone to human error. They seldom provide continuous, item-level verification that each chemical or component is stored in the correct hazard class compartment, nor do they ensure that local environmental conditions (temperature, humidity, gas concentration) inside each compartment remain within prescribed limits. As a result, latent non-compliance (for example, a medium-risk acid placed in a low-risk bin) may persist unnoticed until it manifests as an alarm or incident.

Earlier laboratory safety solutions (including sensor- and dashboard-centred IoT monitoring) have raised situational awareness, yet they typically operate at room or building scale, emphasize hazard detection rather than storage-rule enforcement, and seldom quantify alert selectivity (false-alarm behavior). In particular, prior systems generally do not bind a specific tagged item to a designated hazard-zone compartment and verify its placement while simultaneously assessing compartment-level environmental thresholds leaving a practical gap between environmental monitoring and the enforcement of HSSE storage policies (Cahyadi et al., 2021; Kamel et al., 2022; Odoh et al., 2023; Shaban, 2024). In the Indonesian context, Government Regulation No. 22 of 2021 sets requirements for environmental protection and the management of hazardous and toxic (B3) materials, including storage and monitoring obligations; our design aligns with these obligations by binding items to designated hazard classes and logging compartment conditions.

To address these gaps, this study develops a compact prototype that combines RFID-based storage-zone verification with environmental sensing at the compartment level. An ESP32-based controller reads three RFID inputs mapped to low-, medium-, and high-risk compartments and monitors temperature humidity and gas levels. Data are streamed to an IoT interface for real-time visualization and notifications (for example, implemented via

Blynk), while rule-based logic triggers local (buzzer) and remote alerts when either (i) a tagged item is placed in the wrong hazard zone or (ii) environmental thresholds are exceeded.

Our contributions are threefold: (1) we propose an integrated item-level enforcement architecture that couples RFID placement verification with multi-sensor monitoring at the storage unit; (2) we perform a scenario-driven evaluation across 18 cases (correct and mismatched placements for representative items) with clear metrics—RFID/tag detection, placement-validation accuracy, buzzer selectivity (false positives), and response time; and (3) we provide quantitative evidence that this approach yields 100 % tag detection and placement validation, an average response time of 2.37 s, and no false alarms under correct placements, establishing baseline performance for selective, low-latency HSSE enforcement in smart laboratory settings. The remainder of this paper details the system design and implementation, experimental protocol, results and discussion, and implications for scale-up.

The development of an IoT-based prototype for optimizing hazardous materials and equipment storage is crucial in enhancing Health, Safety, and Environment (HSE) in laboratories, aligning with global standards such as ISO 45001:2018 on occupational health and safety management systems ([ISO 45001:2018 Occupational Health and Safety Management Systems – Requirements with Guidance for Use, 2018](#)) and national regulations like Government Regulation No. 22 of 2021 on Environmental Protection and Management ([Indonesia, Pemerintah Pusat, 2021](#)). Previous studies demonstrate the effectiveness of IoT integration in laboratory safety through fire detection ([Cahyadi et al., 2021](#); [Kamel et al., 2022](#); [Kok et al., 2025](#); [Nadakuditi et al., 2025](#); [Susantok et al., 2025](#); [Udurume et al., 2025](#); [Vorwerk et al., 2023](#)), environmental monitoring ([Ali et al., 2025](#); [Dolińska et al., 2025](#); [Govindarajan et al., 2025](#); [Hussein et al., 2024](#); [Miller et al., 2025](#); [Odoh et al., 2023](#)), and chemical laboratory smart systems ([Shaban, 2024](#)). Moreover, IoT-driven safety innovations such as Smart vessel for fire suppression ([Pisonero et al., 2023](#)) highlight the transformative potential of connected devices in risk mitigation. These advancements address persistent challenges in laboratory safety, including insufficient awareness and unsafe practices among academic stakeholders ([Abduelrahmana et al., 2024](#); [Bilen, D., 2024](#); [Rampean & Rohaeti, 2025](#); [Walters et al., 2017](#); [Wang et al., 2025](#); [Yang et al., 2019](#)), thereby providing a foundation for a more sustainable and technologically adaptive approach to HSE management.

## Research Method

### Research Approach

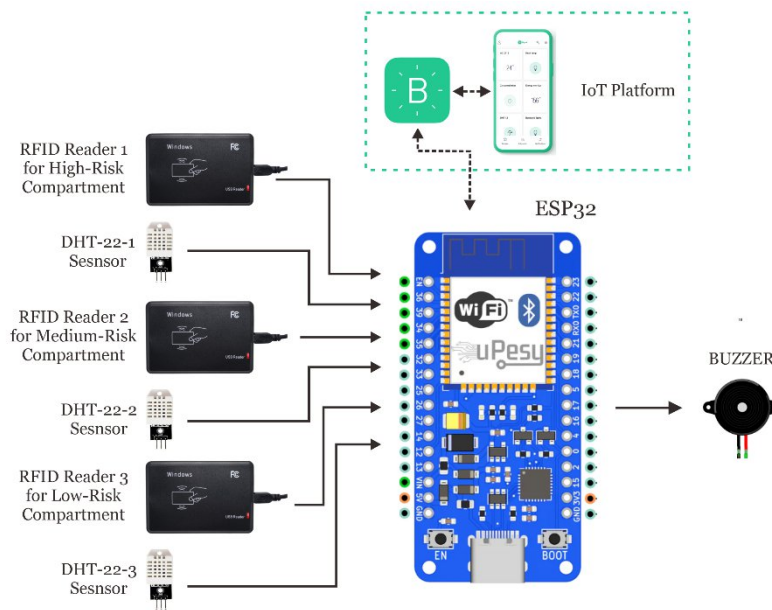
This study employed a quantitative, experimental approach to design and evaluate an IoT-based hazardous-storage monitoring system. The prototype was assembled and tested in

a controlled laboratory environment at Universitas Sains Indonesia. Measurements of system accuracy, sensitivity and response time were collected under various scenarios to quantify performance. The research was motivated by limitations in earlier IoT-based laboratory safety systems, which were often reactive and lacked predictive storage management ([Cahyadi et al., 2021](#); [Odoh et al., 2023](#)). Furthermore, these systems were vulnerable to RFID spoofing, neglected key environmental conditions ([Hussein et al., 2024](#)), and did not address broader risks like domino effects or theft within the Industry 4.0 framework (Shaban, 2024). Our method therefore emphasises proactive enforcement of hazard-zone placement and integrated environmental monitoring to mitigate these gaps.

## Prototype Design and Components

The prototype consists of an ESP32 microcontroller (ESP WROOM 32) connected to three RFID readers (MFRC522 modules) and a set of environmental sensors. Each RFID reader is assigned to monitor one storage compartment, corresponding to a specific hazard level: low, medium, or high. The environmental monitoring system incorporates DHT22 digital sensors installed in each compartment to measure temperature within a range of  $-40^{\circ}\text{C}$  to  $+80^{\circ}\text{C}$  with an accuracy of  $\pm 0.5^{\circ}\text{C}$ , as well as humidity within a range of 0–100 %RH with an accuracy of  $\pm 2$  %RH. In addition, an MQ-135 gas sensor is positioned near the high-risk compartment to detect volatile organic compounds (VOCs) and identify potential gas leaks. This sensor was calibrated using clean air and a certified reference gas (ammonia) to establish both baseline voltage and threshold values for accurate detection.

All sensors and RFID readers were powered via a regulated 3.3 V supply, with logic-level shifting where necessary. The ESP32 was programmed using the Arduino IDE. Sensor readings and RFID data were transmitted over Wi-Fi to a cloud-based IoT interface (implemented via Blynk but designed to be platform-agnostic). The dashboard provides real-time visualisation and allows remote notification via push messages or email. This architecture directly addresses earlier systems' weaknesses by enabling predictive storage management the system not only detects alarms but continuously verifies that each tagged item is in its designated hazard zone and monitors compartment conditions to predict unsafe trends. The complete system architecture is illustrated in the following Figure 1, which presents the prototype's block diagram.



**Figure 1 The System Prototype Block Diagram**

## Hazard-Level Categorisation

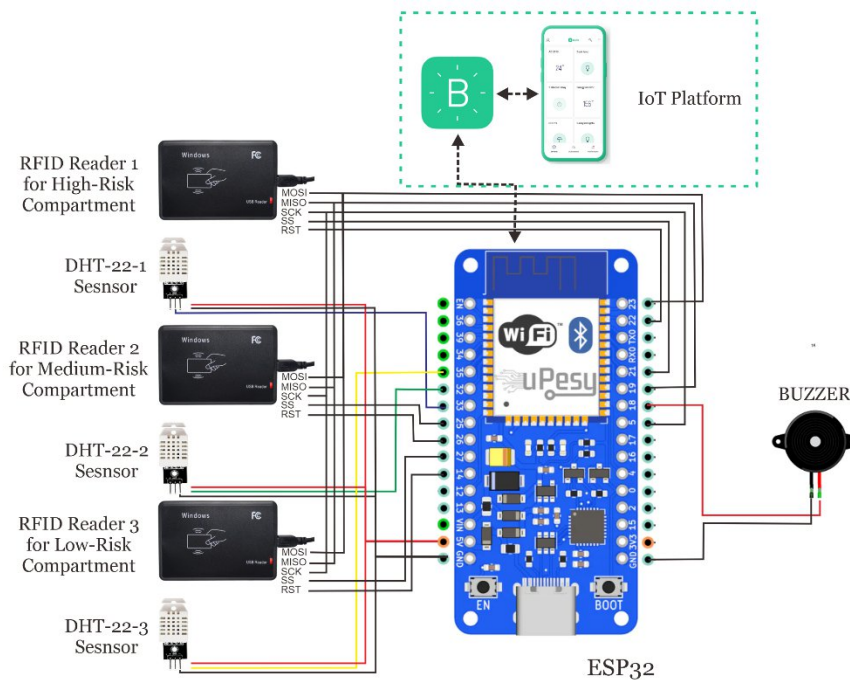
Consistent with Government Regulation No. 22 of 2021 on the management of hazardous and toxic materials (B3) in Indonesia, laboratory materials in this study were categorised into three hazard levels. The low-risk category comprised non-reactive electronic components, such as resistors and capacitors. The medium-risk category included moderate-hazard chemicals, such as hydrochloric acid, sulfuric acid, and isopropyl alcohol, which require controlled storage and the use of personal protective equipment (PPE). The high-risk category consisted of items with significant thermal or chemical hazards, including lithium-ion batteries, concentrated acids or bases, and pressurised gas cylinders.

RFID tags were affixed to each item and encoded with a unique identifier and hazard level. When an item is placed in a compartment, the corresponding RFID reader checks the tag's hazard level against the compartment's classification. Threshold values for temperature, humidity and gas concentrations were set based on manufacturer recommendations and occupational-safety guidelines (e.g., for battery storage and chemical stability). This categorisation ensures compliance with national regulations while operationalising item-level enforcement that prior prototypes lacked.

## Circuit and Connectivity

The circuits design integrates the ESP32 microcontroller with RFID readers, environmental sensors, and output devices, as illustrated in Figure 2. Each MFRC522 RFID reader communicates with the ESP32 via the SPI bus, with dedicated chip-select pins. DHT22 sensors

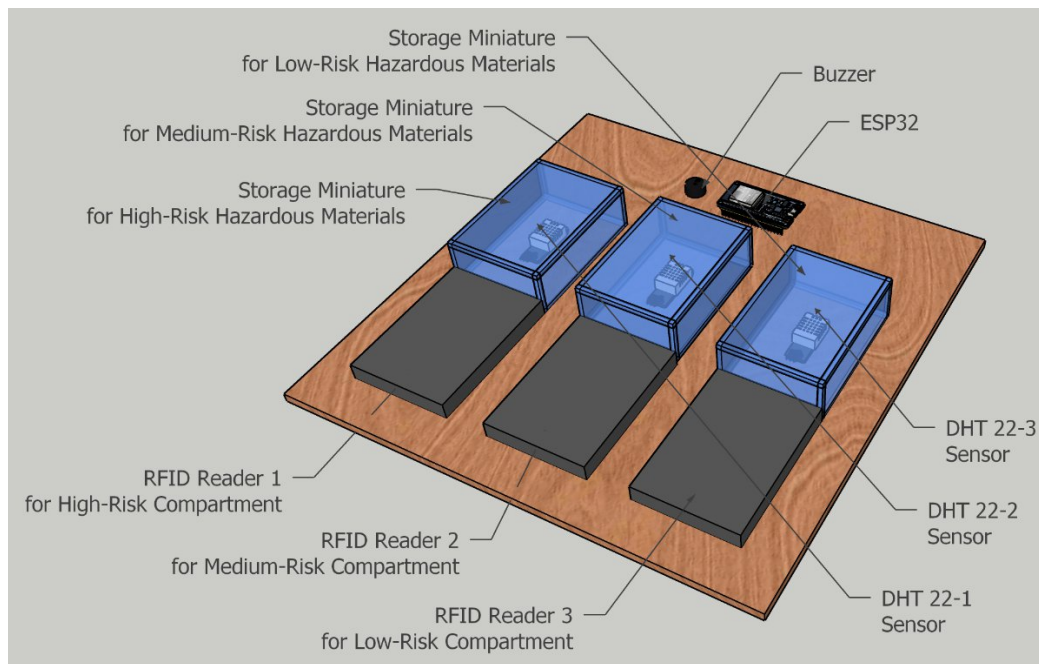
connect to individual digital input pins, while the MQ-135 sensor output is read via an analogue pin. A piezo buzzer serves as the local alert actuator and is driven by a transistor for adequate current handling. All grounds are common to prevent differential offsets. Wi-Fi connectivity is established through the ESP32's integrated radio; secure communication uses Transport Layer Security (TLS). By integrating RFID and sensor data in a single microcontroller, our system avoids the vulnerabilities to tag spoofing and lack of humidity/pressure monitoring that hampered the RFID-authenticated safety system of (Hussein et al., 2024).



**Figure 2 The System Prototype Wiring Diagram**

## Mechanical Layout Design

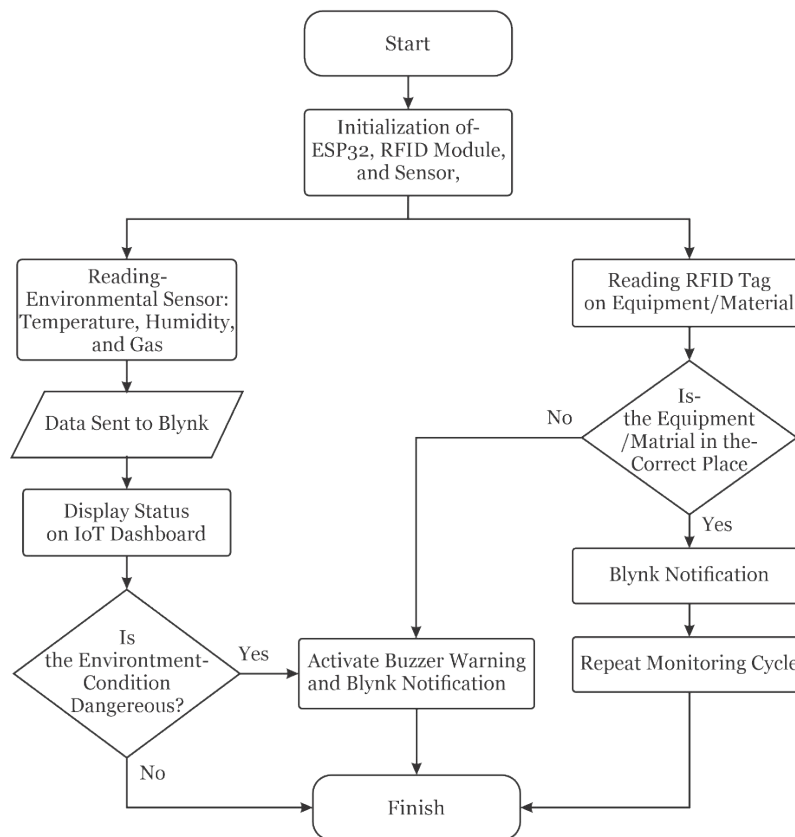
The prototype storage compartments is designed to use acrylic sheets and divided into three compartments (10 cm × 10 cm × 15 cm each), designed as storage miniatures to represent different hazard levels. Each compartment was lined with non-reactive plastic and clearly labeled according to hazard classification. DHT22 sensors were mounted on the rear wall of each compartment for unobstructed airflow, while RFID readers were installed at the front (door side) to detect tag insertion and removal. An MQ-135 sensor was positioned near the top of the high-risk compartment to sense rising gases. The ESP32 controller, buzzer, and power circuitry were housed in a separate enclosure above the compartments to isolate heat and electrical interference. The complete configuration of this prototype layout is illustrated in Figure 4.



**Figure 4 Prototype Mechanical Layout with Storage Miniatures Design**

## Operational Flow and Control Logic

The operational flow of the proposed prototype, illustrated in Figure 5, outlines a structured sequence that governs the system's monitoring and hazard prevention processes. The flowchart demonstrates how the ESP32 microcontroller, RFID readers, and environmental sensors work in unison to ensure that hazardous and toxic materials are stored correctly and that environmental conditions remain within safe thresholds. This structured approach enables proactive hazard prevention, overcoming the reactive limitations observed in earlier systems (Cahyadi et al., 2021; Odoh et al., 2023).



**Figure 5 The System Flowchart**

As Figure 5 presents, the system operates according to the following steps:

1. Initialisation – The ESP32 boots, configures Wi-Fi, and establishes communication with the IoT interface.
2. Tag scanning – Each RFID reader polls for tag presence. When a tag is detected, its hazard level is compared with the compartment's classification.
3. Environmental sensing – Temperature, humidity, and gas readings are sampled from the sensors.
4. Decision rule – If the tag's hazard level matches the compartment and environmental readings are within safe thresholds; the system logs the event and continues monitoring. If a mismatch or threshold violation occurs, an alert state is entered.
5. Alerts and notifications – The buzzer emits an audible warning. A warning message with details (item ID, hazard level, compartment ID, sensor readings) is sent to the IoT interface and forwarded to subscribed users via push notifications or email.
6. Data logging – All events and sensor values are logged locally on an SD card and remotely in the IoT database for future analysis.
7. Loop – The system returns to Step 2 and continues monitoring.

## Experimental Procedures

Testing occurred in a temperature-controlled laboratory ( $24 \pm 1^\circ\text{C}$ ,  $60 \pm 3\% \text{RH}$ ). Three classes of items electronic components (resistor, capacitor), chemicals (hydrochloric acid, sulfuric acid, isopropyl alcohol) and energy storage (lithium-ion battery)—were tagged and placed into the compartments. Each item was tested in three scenarios: placement in the correct compartment, placement in an incorrect compartment (mismatched hazard level), and removal/placement events. Additional tests assessed gas-detection performance by introducing a calibrated gas source to simulate a leak. For each scenario, system responses (sensor readings, tag detections, alert generation) were recorded for 10 repetitions to capture variability.

Furthermore, the performance of the prototype was quantified using several key metrics. RFID detection accuracy was measured as the ratio of successful tag reads to the total number of attempts. Placement validation accuracy referred to the ratio of correct hazard zone classifications to the total number of placements. Buzzer sensitivity was defined as the ratio of correct alerts (true positives) to the total number of misplacement events. The false positive rate represented the fraction of alerts triggered during correct placements. Finally, response time was measured as the interval between the occurrence of an event—such as tag placement or a threshold violation and the activation of an alert, using a high-resolution timer with an accuracy of  $\pm 0.1$  seconds, and the results were averaged over multiple trials.

Statistical analyses (mean, standard deviation) were computed for each metric. A system-level performance index was derived by combining these metrics using weighted averages to facilitate comparison with future system iterations. By reporting both detection accuracy and false positives, our analysis addresses the lack of alert-selectivity reporting noted in earlier studies ([Cahyadi et al., 2021](#); [Hussein et al., 2024](#); [Odoh et al., 2023](#); [Shaban, 2024](#)).

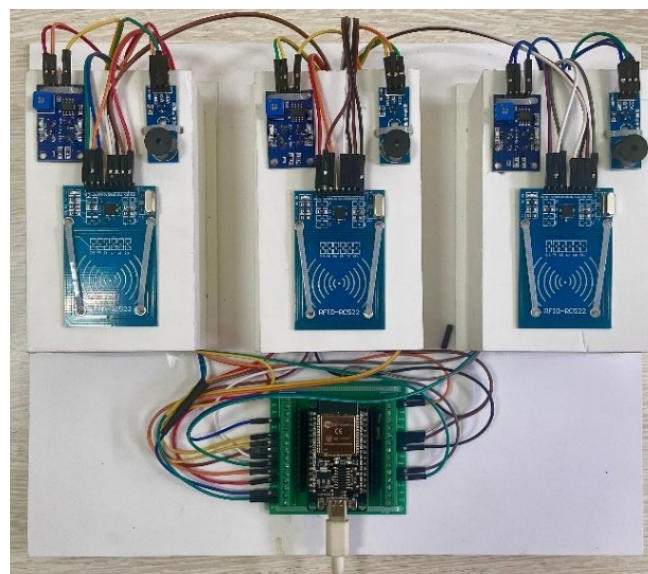
## Result and Discussion

This section presents the mechanical implementation, experimental results and performance analysis of the proposed IoT-RFID prototype. To improve clarity and academic rigour suitable for a SINTA-3 journal, results are organised thematically and cross-referenced with the original figures and table.

### System Prototype Implementation

The physical prototype is assembled to realise a compact, modular storage unit capable of enforcing hazard-zone compliance. Figure 6 illustrates the completed mechanical assembly,

with its key functional components highlighted. The prototype consists of the following core elements: (1) Three distinct storage compartments, visually separated and labeled for low, medium, and high-risk materials. (2) An RFID reader (MFRC522 module, visible as a purple board) is installed at the front of each compartment to scan tags on items as they are placed inside. (3) A DHT22 sensor (a small blue module) is mounted inside each compartment to monitor temperature and humidity. (4) An MQ-135 gas sensor is positioned above the high-risk compartment to detect potential leaks of volatile compounds. (5) The system is coordinated by a central ESP32 microcontroller (the large green board), which processes all sensor and RFID data. (6) A local piezo buzzer (the black cylinder) provides immediate audible alerts for any safety violations, such as a misplaced item or dangerous environmental conditions. This arrangement adheres to ergonomic principles, enabling intuitive placement and retrieval of materials while segregating risk categories. The modular design allows for scalability and facilitates replacement of individual sensors or readers without dismantling the entire unit. The prototype thus provides a tangible foundation for enforcing Health, Safety, Security and Environment (HSSE) policies in laboratory settings.



**Figure 6 The Implemented System Prototype.** Key components are indicated: (1) Hazard-level compartments, (2) RFID readers, (3) DHT22 temperature-humidity sensors, (4) MQ-135 gas sensor, (5) ESP32 microcontroller, and (6) Alert buzzer.

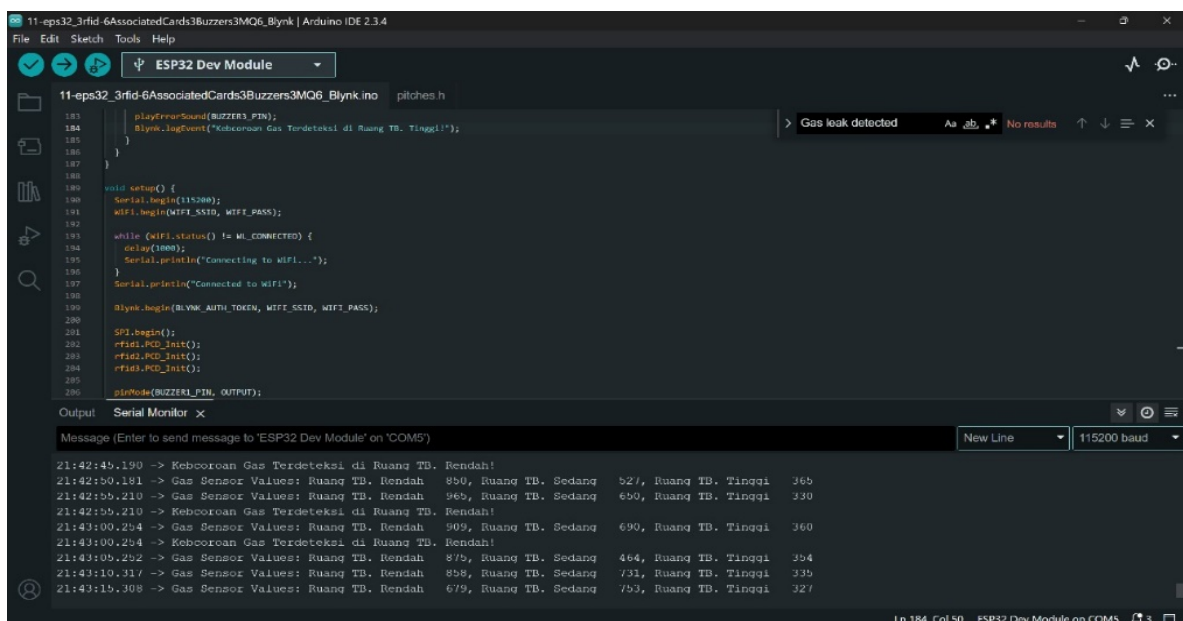
Controlled gas-leak experiments were conducted to validate the response of the prototype's environmental sensing subsystem. During these tests, a calibrated gas source was introduced near the high-risk compartment while the system operated in monitoring mode. Figure 7 shows the test setup, where the sensor modules emit visual indicators as gas concentrations increase and a user simultaneously observes the system's behaviour. The prototype

transmitted sensor readings to the IoT interface in real time and triggered audible and remote alarms once concentrations exceeded the safety threshold.



**Figure 7 Gas-leak testing of the prototype. A controlled gas source was applied to verify sensor responsiveness and alert mechanisms.**

The embedded controller logs sensor data continuously and dispatches it to the cloud dashboard. Figure 8 presents a screenshot of the monitoring interface during gas detection. The serial monitor output from the ESP32 (upper pane) shows code execution and Blynk event logging, while the lower pane records time-stamped warnings triggered by gas detection events. This experiment confirms that the system recognises hazardous conditions promptly, publishes alerts to the IoT dashboard and activates local warnings without manual intervention.



**Figure 8 Real-time sensor data and warning messages captured during gas detection. The system logs events and publishes alerts via the IoT interface.**

## RFID-Based Material Storage Validation

To evaluate the item-level storage enforcement, a series of experiments assessed system behaviour when different materials were placed in correct and incorrect compartments. Each test combined RFID identification with hazard-level verification and environmental monitoring.

### Material Correct Placement Test

The third scenario assessed system behaviour when a medium-risk chemical (HCl) was placed in the correct medium-hazard compartment. Figure 9 depicts this test. The RFID reader identified the tag, verified hazard compatibility, and continued monitoring. No alerts were triggered, and sensor readings remained within safe ranges. This confirms the system's ability to discern between appropriate and inappropriate placements and avoid unnecessary warnings.



**Figure 9. Medium-risk material correct placement test. The HCl tag matched the medium-risk compartment, and no alerts were generated.**

Additionally, Figure 10 shows the scenario where a capacitor (low-risk material) was placed in its designated low-hazard compartment. The IoT dashboard confirmed that the material was correctly stored, and no alarms were triggered. Environmental readings remained within safe bounds, demonstrating that the system can reliably permit access to non-hazardous items while continuing to monitor conditions.



**Figure 10. Low-risk material placement test. The capacitor's RFID tag matched the low-hazard compartment and no alarm was raised.**

### Material Misplacement Test

In another experiment, hydrochloric acid (HCl), classified as medium risk, was intentionally stored in the low-risk compartment to test the system's error detection. Figure 11 illustrates this misplacement scenario. The system identified the mismatch between the tag's hazard level and the compartment's classification, logged the event, and activated an alert on the buzzer and dashboard. Importantly, no gas was detected during this test, indicating that the alert resulted solely from hazard-level misclassification. This demonstrates the prototype's ability to enforce storage policies proactively.



**Figure 11. Medium-risk material misplacement test. The system detected the hazard-level mismatch and issued an alarm despite normal environmental readings.**

Furthermore, the prototype's performance was tested when a medium-risk chemical (sulfuric acid) was placed in the high-risk compartment. As shown in Figure 12, the system detected that the chemical's classification did not correspond to the high-risk compartment and issued a visual alert. This highlights that the prototype enforces both upward and downward mismatches; although sulfuric acid poses less risk than high-risk items (e.g., lithium-ion batteries), the system still flagged the misplacement as a procedural error. Such enforcement prevents arbitrary storage and reduces cross-contamination risks.



**Figure 12.** High-risk compartment test. The system flagged the placement of a medium-risk material in a high-risk compartment as non-compliant.

## Summary of Experimental Results

Quantitative results from all 18 test scenarios are summarised in Table 1. Each row corresponds to a material–compartment combination and reports the response time from tag placement to alert (or confirmation) and whether the system correctly validated the storage. The results indicate perfect RFID read success and hazard-level validation across all tests. Average response time across scenarios was approximately 2.37 s, well below the 3 s threshold typically recommended for early hazard detection systems. The buzzer activated selectively during misplacement or threshold violations, yielding a buzzer sensitivity of 100 % and zero false positives during correct placements. These metrics underline the prototype's capability to enforce HSSE protocols with high reliability and minimal latency.

**Table 1 Summary of test scenarios, system responses and outcomes**

No	Material	Material Hazard Level	Storage Compartment (Hazard Level)	RFID Reading Status	Response Time (s)	Buzzer Status	Description
1	Resistor	Low	Low	Detected	1.2	1	Correct placement (low risk)
2	Resistor	Low	Medium	Detected	2.5	2	Misplacement detected
3	Resistor	Low	High	Detected	2.4	3	Misplacement detected
4	Capacitor	Low	Low	Detected	1.1	4	Correct placement (low risk)
5	Capacitor	Low	Medium	Detected	2.3	5	Misplacement detected
6	Capacitor	Low	High	Detected	2.6	6	Misplacement detected
7	Alcohol	Medium	Low	Detected	2.7	7	Misplacement detected
8	Alcohol	Medium	Medium	Detected	1.3	8	Correct placement (medium risk)
9	Alcohol	Medium	High	Detected	2.8	9	Misplacement detected
10	HCl	Medium	Low	Detected	2.9	10	Misplacement detected
11	HCl	Medium	Medium	Detected	1	11	Correct placement (medium risk)
12	HCl	Medium	High	Detected	2.5	12	Misplacement detected
13	H <sub>2</sub> SO <sub>4</sub>	Medium	Low	Detected	2.6	13	Misplacement detected
14	H <sub>2</sub> SO <sub>4</sub>	Medium	Medium	Detected	1.2	14	Correct placement (medium risk)
15	H <sub>2</sub> SO <sub>4</sub>	Medium	High	Detected	2.4	15	Misplacement detected
16	Battery	High	Low	Detected	2.8	16	Misplacement detected
17	Battery	High	Medium	Detected	2.7	17	Misplacement detected
18	Battery	High	High	Detected	1.3	18	Correct placement (high risk)

The dataset underscores that all RFID tags were successfully read and validated. The system correctly identified mismatched hazard levels in 11 of the 18 tests, triggering audible and remote alerts only when required. Response times varied slightly by scenario but remained within 1–3 s, demonstrating low latency across diverse hazard categories. Statistical analysis yielded a mean response time of 2.37 s with a standard deviation of 0.71 s. These results support the claim that the system provides timely warnings, aligning with HSSE requirements for rapid incident mitigation.

To formalise system evaluation, several metrics were computed. RFID reading accuracy ( $A_{\text{RFID}}$ ) is defined as the ratio of successful tag reads to total attempts, expressed in Equation

(1). Validation accuracy (  $A_{val}$  ) quantifies the proportion of correct hazard-zone classifications. Buzzer sensitivity (  $S_{buzzer}$  ) measures the ratio of correct alerts to total misplacement events. The false positive rate (FPR) captures the fraction of alerts generated during correct placements (ideally zero). Finally, average response time (  $t_{response}$  ) is computed from individual response measurements.

$$A_{RFID} = \frac{N_{read}}{N_{total}} \times 100\%, A_{val} = \frac{N_{correct}}{N_{total}} \times 100\%, S_{buzzer} = \frac{N_{correct\ alerts}}{N_{misplacements}} \times 100\%$$

$$FPR = \frac{N_{false\ alerts}}{N_{correct\ placements}}, t_{response} = \frac{1}{N} \sum_{i=1}^N t_i \quad (1)$$

Across all scenarios,  $A_{RFID}$ ,  $A_{val}$  and  $S_{buzzer}$  each achieved 100%, while FPR was 0%. The average response time  $t_{response}$  was 2.37 s. These metrics collectively demonstrate that the prototype ensures accurate identification, hazard classification and selective alerting with minimal latency.

Two aggregated performance indices were also evaluated. A system score combines accuracy, sensitivity, false-positive rate and response time using weighted coefficients (  $w_1 - w_5$  ) to facilitate comparison across prototypes. The Fuggi Index averages the core metrics  $A_{RFID}$ ,  $A_{val}$  and  $S_{buzzer}$ , providing an overall performance percentage. Both indices yielded maximum values (100 %), confirming the prototype's robustness. These quantifiable benchmarks are useful for iterative improvements and cross-study comparisons.

## Discussion and Implications

The experimental findings highlight the advantages of integrating RFID-based placement verification with multi-sensor monitoring in hazardous-storage applications. The prototype outperforms earlier IoT-based laboratory safety systems, which were primarily reactive and lacked item-level enforcement. By combining RFID identification with compartment-level environmental sensing, the system prevents misplacement before hazardous conditions arise. The absence of false positives contrasts with many previous IoT alarm systems that suffer from nuisance alerts due to ambient fluctuations (Cahyadi et al., 2021; Odoh et al., 2023). For instance, unlike the system by (Cahyadi et al., 2021), which focused on reactive fire detection at the room level, our prototype prevents incidents through proactive, item-level storage rule enforcement. This integrated approach of RFID and environmental monitoring addresses the gap identified by (Odoh et al., 2023), who monitored the lab environment but did not link

conditions to specific stored items or verify their correct placement. Furthermore, while (Shaban, 2024) developed a smart chemical laboratory system, it did not explicitly address the validation of hazard-zone compliance or report on false-alarm rates, which are key contributions of our work. The quick response times and high sensitivity confirm that the proposed approach is suitable for real-time HSSE enforcement.

The current prototype validates the concept at a single storage-unit level. A critical consideration for real-world impact is its scalability to larger laboratories with extensive inventories, high item turnover, and diverse stock. Scaling this system would involve addressing several key challenges. First, RFID reader coordination is essential to prevent signal collision when multiple tags are present simultaneously; this can be mitigated by employing readers with advanced anti-collision algorithms and scheduling read cycles strategically. Second, the network architecture would need to evolve from a single ESP32 controller to a hierarchical structure. Multiple storage units could be managed by local gateways (e.g., one ESP32 per shelf or cabinet), which then aggregate and transmit data to a central lab server, reducing WiFi congestion and improving reliability. Third, handling the increased data flow would benefit from edge computing principles, where basic validation rules (e.g., tag-compartment matching) are processed locally at the gateway level, and only alerts and logged events are sent to the cloud, minimizing latency and bandwidth use. Finally, the physical layout must remain ergonomic; the proposed modular design allows units to be deployed as standalone cabinets or integrated into existing shelving systems. While the controlled environment provided a valid proof-of-concept, future trials in active laboratory settings with multiple users and concurrent storage events are the essential next step to validate these scaling strategies and the system's performance under real-world conditions.

Several limitations and potential failure modes must be considered for robust deployment. Firstly, the system currently lacks sensor redundancy. A failed sensor could create a false sense of security. Future iterations should incorporate cross-validation between sensors or diagnostic self-checks to detect failures. Secondly, the scenario of multiple simultaneous alerts (e.g., a gas leak occurring during a material misplacement) requires a prioritization logic that we did not implement; a hierarchical alerting system would be necessary to ensure critical warnings are not missed. Thirdly, from a security perspective, the current system is vulnerable to threats such as RFID tag spoofing or cloning, and network attacks on the IoT data stream. Mitigating these would require implementing cryptographic authentication for tags (e.g., using more advanced NFC tags) and ensuring all network communications are secured with strong encryption (TLS) and regular security updates. Finally, the long-term stability of low-cost sensors like the MQ-135 in variable environmental conditions is a known challenge;

periodic calibration would be essential for sustained accuracy. Addressing these limitations is crucial for transforming the prototype into a resilient safety-critical system. These results also underscore the importance of selective alarms. Alerts were triggered only when a material was placed in the wrong compartment or when gas concentrations exceeded safe limits. Such selectivity is vital in laboratory environments to avoid alert fatigue and ensure that users trust and respond to warnings. The system's zero false-positive rate demonstrates that the decision logic successfully distinguishes between safe and unsafe conditions.

Although the prototype achieved excellent performance, several improvements could enhance its robustness and scalability. First, additional environmental sensors (e.g., pressure and vibration) could complement temperature, humidity and gas measurements, further reducing undetected hazards. Sensor redundancy and cross-validation would mitigate single-point failures and spoofing attempts. Second, integration with cloud-based analytics and machine-learning algorithms could enable predictive maintenance, anomaly detection and trend analysis. Third, energy-efficient firmware and sleep modes would extend battery life for standalone deployments. Finally, trials in diverse laboratory environments with larger inventories and different hazard classes are recommended to validate generalisability.

In summary, the prototype demonstrates that combining RFID-assisted placement verification with real-time environmental sensing yields a proactive, low-latency safety system. The results provide quantitative evidence of its suitability for smart laboratories and align with HSSE requirements for rapid detection, selective warning and compliance enforcement.

## Conclusions

The findings of this study demonstrate that a compact prototype combining radio-frequency identification with multi-sensor environmental monitoring can provide highly reliable, low-latency enforcement of hazardous-materials storage rules in laboratory settings. Testing across a range of materials and hazard categories showed perfect tag detection and correct placement validation, with no false alarms and response times on the order of a few seconds. By verifying that each item is stored in its designated hazard-zone compartment while simultaneously assessing local temperature, humidity and gas conditions, the system moves beyond the reactive detection focus of earlier IoT solutions and delivers proactive HSSE control. Its modular construction, ergonomic layout and cloud-connected interface make it readily scalable and adaptable to different laboratory environments, marking a meaningful contribution to the development of smart laboratories and to the broader field of technology-driven health, safety, security and environmental (HSSE) management.

While the prototype performed robustly under controlled conditions, future work should broaden its scope and enhance its resilience. The immediate next steps include large-scale trials in diverse, active laboratories to validate scalability and user interaction studies to understand how personnel respond to and trust the system's alerts. From a technical perspective, integration with cloud-based analytics and machine learning would enable predictive maintenance (e.g., forecasting sensor drift) and early anomaly detection, further shifting the system from responsive to anticipatory safety. Energy-efficient firmware and sleep modes are also needed to support standalone battery-powered deployments in areas without constant power. To address security and robustness, future designs must incorporate redundant sensors, advanced authentication protocols to prevent spoofing, and hierarchical alert prioritization. Together, these refinements can transform the present prototype into a comprehensive platform for safeguarding laboratories and advancing scientific practice through intelligent HSSE enforcement.

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