

Digital-twin-based Intelligent Laboratory Management Framework Using 3D Scanning and IoT Sensors

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Previous research laboratories suffer from space inefficiency, disorganized asset tracking, and inefficient safety monitoring. To apply digital twins in a research laboratory, signal degradation in metallic environments and manual model updating must be addressed. Therefore, we developed an intelligent management framework for research laboratories by integrating 3D scanning with IoT sensors in a digital twin. Laser scanning and photogrammetry were used to establish a 3D spatial model with an average absolute error of 8.2 mm and a relative error of 0.28%. A heterogeneous IoT network was included to synchronize real-time data in the 3D model. The IoT network comprised Bluetooth low energy beacons, equipment status monitors, and environmental sensors. The developed framework showed an average positioning accuracy of 0.71 m and recognized equipment power and vibration states with accuracies of 98 and 95%, respectively. The framework decreased equipment search time by 86.7% and inventory processing time by 87.5%, whereas space utilization increased by 18%. By integrating high-precision spatial models with IoT sensors, laboratory operations are advanced from reactive manual routines to data-driven predictive management. The framework can be improved to overcome interference in high-density metallic zones and introduce automated spatial calibration. This necessitates the integration of autonomous simultaneous localization and mapping, predictive deep learning models for asset maintenance, and precise simulations into the digital twin.

1. Introduction

Well-designed laboratories foster innovative thinking and support various science and engineering research, such as model fabrication, digital construction, human–computer interaction, and material research. Laboratories are typically equipped with advanced instruments, whereas workstations, 3D printers, and virtual/augmented reality (VR/AR) devices are also increasingly adopted.⁽¹⁾ Despite the technological sophistication of instruments in

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laboratories, the management of laboratories mainly relies on manual registration and periodic inventory. Such traditional management faces challenges that hinder the enhancement of efficiency, safety, and resource utilization.^(2,3)

Conventional laboratory management often lacks efficient resource allocation, especially in space allocation. Inflexible zoning methods fail to allocate areas for specific functions when research and teaching needs change. This makes several zones overcrowded, whereas others are underused.⁽⁴⁾ Similar problems are also observed in the asset management of a laboratory. Manual inspections are used for diverse equipment, which is error-prone and unable to prevent failures or idle resources, hindering the effective use of teaching assets.⁽⁵⁾ Researchers have proposed separate system architectures for intelligent laboratory management with limited integration. Radio frequency identification and standalone Bluetooth low energy (BLE) sensor networks are widely used to monitor equipment and environmental data but lack spatial and geometric visualization data.⁽⁶⁾ Building management platforms are also used to provide detailed 3D models of a laboratory, but the platforms require static updates and rarely incorporate real-time equipment or environmental data.⁽⁷⁾ In vision-based tracking methods, sensors are not included, which causes occlusions in crowded layouts.⁽⁸⁾

Such problems stem from the absence of real-time monitoring,⁽⁹⁾ which also results in inadequate environmental monitoring during high-risk operations, including laser cutting and hazardous chemical handling. Furthermore, the limited level of informatization and visualization constrains efficient laboratory management. Without a unified information platform, it is difficult to design effective spatial layouts to determine device locations and assess equipment availability.⁽¹⁰⁾

Recent advances in 3D scanning and IoT sensor technologies enable promising solutions to these challenges. 3D scanning enables the rapid and precise acquisition of geometric and textural data in laboratory environments, enabling the construction of digital twin models of laboratory spaces.⁽¹¹⁾ Through the integration of sensor data, IoT technology enables connections between equipment and platforms, enabling the real-time monitoring of environmental conditions and equipment status.⁽¹²⁾ These technologies facilitate the development of intelligent management systems that remain synchronized with physical laboratories, integrating virtual and physical dimensions.⁽¹³⁾ The systems with these technologies have enhanced spatial utilization, asset management, and safety monitoring, requiring the advancement of sensor technology to maintain intelligent, adaptive, and secure laboratory environments.

In this study, we developed an intelligent laboratory management framework by combining high-precision 3D scanning with an IoT network. Spatial geometries were adopted to stabilize BLE positioning, whereas sensors were used to capture the operational status of equipment in real time. This integration enables the construction of models for dynamic asset monitoring and the effective management of space and resources. On the basis of advanced technologies, the developed framework in this study realizes the potential of sensor-based systems in laboratory management. The results of this study present the role of sensor technology in constructing an intelligent laboratory and advancing educational and industrial technologies.

2. Methods

2.1 Platform design

In this study, we designed a visual, intelligent, and automated laboratory management platform. In the design, the following principles were applied to ensure accurate 3D modeling, real-time IoT data collection, flexible system expansion, intuitive user interaction, and reliable long-term operation: high precision and immediacy, scalability and modularity, user-friendliness, stability and reliability, and cost-effectiveness with ease of maintenance. We introduced a layered architecture in the laboratory design platform at the following levels: physical perception, data transmission, data processing and service, and application and visualization (Fig. 1).

1. Physical perception layer: This layer converts physical statuses into digital signals. Data are acquired using handheld laser scanners and high-resolution digital cameras to collect point cloud and texture data. IoT sensor nodes are deployed throughout the laboratory, including BLE beacons for asset positioning, smart sockets and vibration sensors for equipment status monitoring, and integrated environmental sensors for temperature, humidity, particulate matter (PM) 2.5, CO₂, and volatile organic carbons (VOCs).
2. Data transmission layer: In this layer, a hybrid network topology is used to ensure reliable communication among equipment and platforms. Gigabit Ethernet is introduced to support high-bandwidth servers and gateways, whereas Wi-Fi provides coverage for BLE gateways, environmental monitors, and user terminals. BLE enables low-power and long-range communication between beacons and gateways to supplement Wi-Fi in blind spots or long-distance connections.

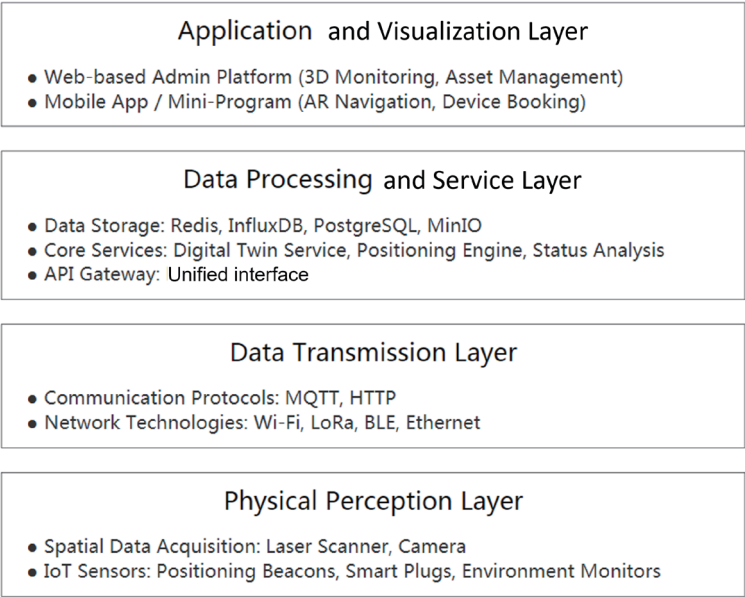


Fig. 1. Platform architecture with four layers (App: application; DB: database; SQL: structured query language; HTTP: hypertext transfer protocol).

- 3. Data processing and service layer: This layer manages data storage, analysis, and services. Sensor data are transmitted through message queuing telemetry transport (MQTT), cleaned, and stored in real-time and time-series databases. Digital twin services are used to map sensor data to 3D models and locate laboratory assets based on received signal strength indicator (*RSSI*)-based trilateration. Statuses in the laboratory are analyzed to monitor equipment operation and issue warnings.
- 4. Application and visualization layer: This layer enables a web-based platform to provide users with functions of 3D visualization, asset management, space planning, equipment reservation, data dashboards, navigation, and alarm notifications

In the platform, 3D reconstruction technology is used to combine high-precision laser scanning and photogrammetry to generate digital twin models optimized for web deployment. Building information management (BIM) and an indoor positioning system are integrated to construct geometric models with semantic information, such as equipment metadata, for intelligent asset management, and *RSSI*-based BLE technology, with multiple gateways forming signal coverage and algorithms calculating real-time asset coordinates.^(12,13)

2.2 3D digital modeling

Laser scanning and photogrammetry were used to ensure geometric accuracy and visual fidelity.^(14,15) Laser scanning was conducted using a FARO Focus S70 scanner (FARO Technologies Incorporated, USA, ± 1 mm accuracy and a 70 m range). Twelve measurement stations were deployed across the 500 m² laboratory with 30% overlap to ensure full coverage. Reflective targets were positioned in overlapping regions as control points for point cloud registration. The scanner was used to capture panoramic 3D coordinates at 976000 points per second, with resolution set to balance acquisition speed and millimeter-level precision. Photogrammetry was applied to record fine surface textures and color maps. A Sony A7R IV full-frame camera fitted with a Sony FE 35 mm F1.8 prime lens was used, fixed at f/8 aperture and International Organization for Standardization 100 to maintain a consistent depth of field and exposure (Table 1). The operator moved along continuous orbital paths around complex equipment and structural elements, maintaining image overlap ratios above 70% laterally and 60% longitudinally. Totally, 2,500 high-resolution images were captured under diffused ambient

Table 1
Equipment and its important parameters for data collection.

Equipment	Model	Parameter	Application
Laser scanner	Faro Focus S70	Accuracy: ± 1 mm Rate: 976,000 presentation time stamps per second Range: 0.6–70 m	Capturing precise point clouds of main spatial structures and large equipment
Digital camera	Sony A7R IV	Resolution: 61 megapixels Sensor: full-frame sensor	Capturing high-resolution texture information and detailed models of small objects
Lens	Sony FE 35mm F1.8	Prime lens	Ensuring consistency in image quality

lighting, minimizing shadows during texture projection. The dataset included an accurate point cloud enriched with high-resolution textures, enabling the precise digital reconstruction of the laboratory environment.

Raw point cloud data are denoised using statistical outlier removal and registered using target balls and the iterative closest point (ICP) algorithm.⁽¹⁶⁾ The ICP algorithm minimizes the error function using the following equation:

$$E(R,t)=\sum_{i=1}^N\| (Rp_i+t)-q_i\|^2.$$

(1)

Here, $E(R,t)$ represents the objective error function to be minimized, N is the total number of identified corresponding point pairs, p_i and q_i are the corresponding point pairs in the source and target point clouds, R is the 3×3 rotation matrix that defines the orientation adjustment, and t is the 3D translation vector representing the positional shift.

To process the data, Poisson surface reconstruction is used to generate watertight triangular meshes.⁽¹⁷⁾ Mesh simplification is applied using quadratic error metrics to reduce complexity while preserving the features of the data. Textures from photogrammetry are projected onto UV maps, and multiple levels of detail (LOD) are created. The final models are converted to graphics language transmission format (glTF) for efficient web visualization (Table 2).⁽¹⁸⁾

2.3 Semantic information annotation and BIM integration

Independent objects are segmented and annotated with metadata.⁽¹⁹⁾ Each object is assigned a unique identification (ID), linked to database records, including asset type, purchase date, responsible person, and real-time IoT data (Table 3, Fig. 2). The data are used for dynamic BIM visualization for users to query detailed information directly from a 3D model.

2.4 IoT sensing network

Three categories of sensors were used in the framework: BLE beacons for asset positioning, smart sockets and vibration sensors for equipment monitoring, and multi-parameter environmental monitors for safety assessment. BLE beacons [Global Tag BEACONY, Italy, radius 40 mm housing, Ingress Protection (IP) 67] were operated at 2.4 GHz with a transmission range up to 200 m, powered by a CR2477 battery with a three-year lifetime. iBeacon/Eddystone protocols were used for accelerometer input and optional temperature/humidity sensing to improve positioning accuracy through

Table 2
Comparison of data before and after processing.

Item	Before processing	After processing	Optimization rate
Point cloud data	Up to 15 gigabytes (GB)	–	–
Initial mesh model	Up to 210 million faces	300,000 faces (LOD)	99.8%
Model file size	Up to 1.8 GB (OBJ)	Up to 25 MB (glTF)	98.6%

Table 3
Identification data for BIM information.

Field name	Example	Description
asset_id	3DP-001	Unique asset ID
asset_name	Ultimaker S5	Equipment name
model_id	model_123	Corresponding object ID in the 3D model
category	3D Printer	Equipment classification
purchase_date	2022-09-01	Date of purchase
status	Idle	Real-time status (from IoT data)
location	(10.5,25.2,1.2)	Real-time coordinates (from positioning engine)
handler	User	Person in charge
manual_url	/docs/ultimaker_s5.pdf	Link to the operation manual

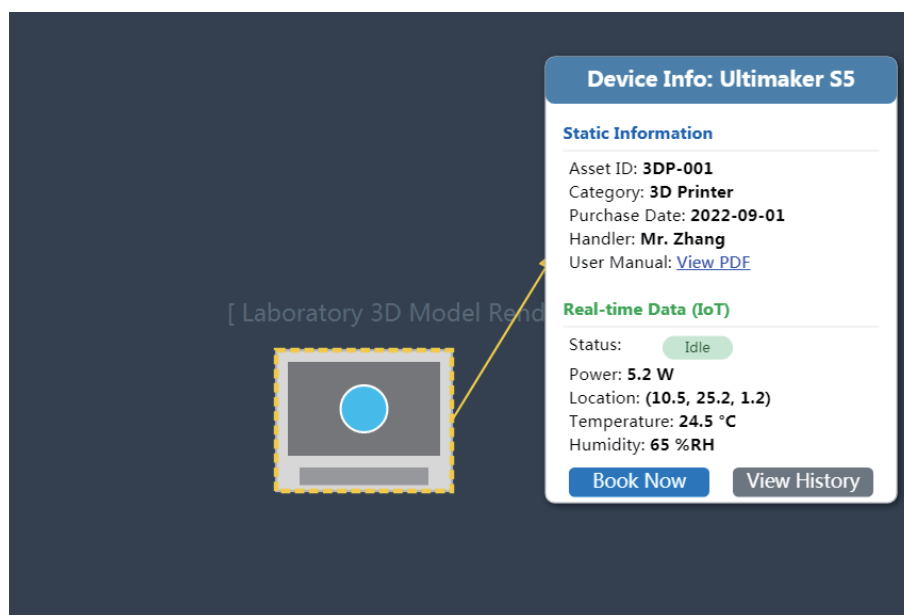


Fig. 2. (Color online) BIM information integration and visualization interface.

RSSI-weighted trilateration. BLE gateways were installed on laboratory ceilings to ensure full coverage. Smart sockets (Zebronics, China, Wi-Fi enabled, 220 V AC, 10 A max load) were used to measure real-time power consumption with $\pm 1\%$ accuracy and remote switch control. Vibration sensors (STMicroelectronics, Switzerland, ST LIS3DH accelerometer, selectable range from ± 2 – $\pm 16g$, 1–5 kHz sampling) monitor operational states of CNC and laser cutting machines, detecting both continuous vibration and transient events. For environmental monitoring, six five-in-one devices (Trax10149 Environmental Sensor Beacon, Finland, IP67 enclosure) were installed in functional zones. Each device is used to measure temperature (-40 to $+100$ °C, ± 0.2 °C accuracy), humidity (0–100% relative humidity, $\pm 4\%$ accuracy), PM2.5, CO₂, and VOCs. Additional onboard sensors include barometric pressure (300–1100 hPa, ± 1 hPa), ambient light, and acoustic noise detection. These devices are battery-powered (1000 mAh, optional USB supply) and support Wirepas Mesh for scalable data collection (Table 4).

Table 4
Equipment and its important parameters for data collection.

Equipment	Model	Parameter	Application
BLE beacons	BEACONY	Radius: 40 mm housing, IP67; 2.4 GHz; Transmission range: up to 200 m; Battery: CR2477 (three year lifetime); Protocols: iBeacon/Eddystone; Optional accelerometer & temp/humidity sensing	Asset positioning via RSSI weighted trilateration; coverage ensured by ceiling mounted gateways
Smart sockets	Zebronics	Wi Fi enabled; 220 V AC; 10 A max load; $\pm 1\%$ accuracy	Real time power consumption monitoring and remote switch control
Vibration sensors	ST LIS3DH accelerometer	Selectable range: ± 2 – ± 16 g; Sampling: 1–5 kHz	Monitoring operational states of CNC and laser cutting machines; detecting continuous vibration and transient events
Environmental monitors	Trax10149	IP67 enclosure; measures: Temp (-40 to $+100$ °C, ± 0.2 °C), relative humidity (0–100% RH, $\pm 4\%$), PM2.5, CO ₂ , VOCs; Additional sensors: Barometric pressure (300–1100 hPa, ± 1 hPa), ambient light, acoustic noise; Battery: 1000 mAh (optional USB supply)	Safety assessment in functional zones; scalable data collection

Sensors and gateways were integrated and tested using MQTT clients. Each sensor's performance was validated by simulating operational changes. Vibration sensors were tested to confirm detection thresholds, smart sockets were toggled to verify power state recognition, and environmental monitors were exposed to controlled changes in temperature, humidity, and gas concentration.

Figure 3 shows the sensor arrangement in the laboratory's 3D model. The laboratory area was divided into three functional zones: the main operation, material/laser cutting, and precision/3D printing zones. BLE gateways were mounted on ceilings in all zones. Environmental monitoring devices were installed throughout each area to collect data on temperature, humidity, particulate matter, CO₂, and VOC levels. Smart sockets were positioned in equipment-intensive zones: one in the material/laser cutting area and two in the precision/3D printing area to measure power consumption and enable the remote control of high-load devices. Vibration sensors were located near CNC and laser cutting machines to detect operational states. BLE beacons are placed strategically to provide asset positioning data, with their signals stabilized by geometric constraints from the 3D scan. Each zone was monitored for environmental safety and equipment performance for gateways and beacons to maintain accurate positioning across the entire laboratory. The integration of heterogeneous sensors in distinct operational areas enabled the capturing of sensor data in real time, linking spatial visualization with asset monitoring (Fig. 3).

3. Results

The developed framework was implemented in a 500 m² digital design and advanced manufacturing laboratory with a ceiling height of 4.5 m. For performance evaluation, operational zones were selected: multi-material additive manufacturing (utilizing fused deposition modeling and stereolithography 3D printers), CO₂ laser cutting and acrylic sheet engraving, precision

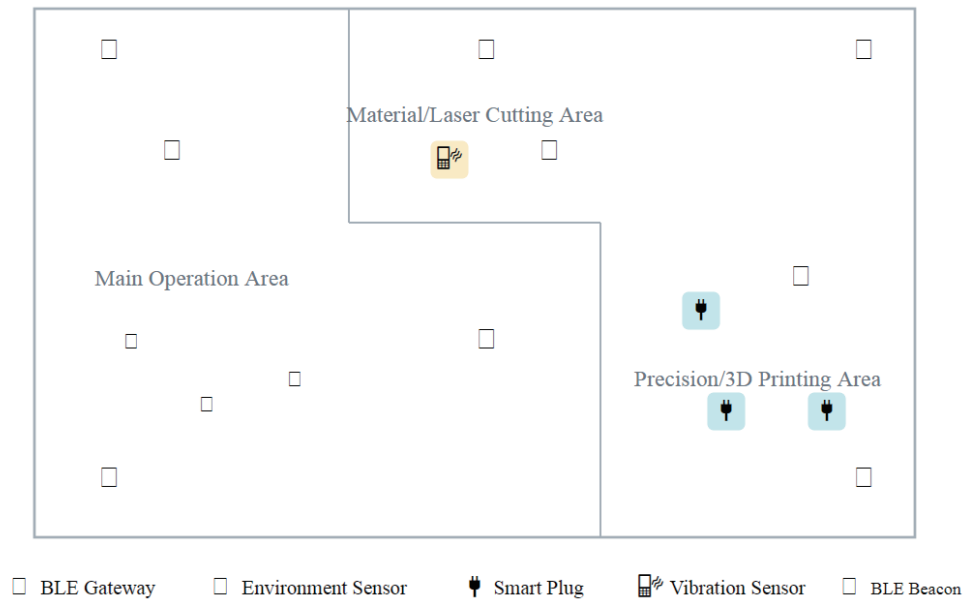


Fig. 3. (Color online) Deployment position of sensors in 3D model of laboratory.

CNC subtractive prototyping, and physical computing assembly. Operational conditions, including thermal fluctuations during 3D printing, airborne particulate matter and VOC emissions during laser cutting, high-frequency vibrations during CNC machining, and electromagnetic signal attenuation caused by metallic storage units and heavy machinery, were monitored. The data were processed using a server configured with an Intel Xeon E5-2680 v4 processor running Ubuntu 22.04 Long Term Support to ensure sufficient computational overhead for real-time data fusion.

To validate the accuracy of the digital twin, the dimensions of the generated 3D model were compared with actual measurements obtained using a high-precision laser rangefinder. Twenty distinct feature points, including structural elements (wall corners, column heights) and fixed assets (door frames), were selected for analysis. The comparison revealed an average absolute error of 8.2 mm and a relative error of 0.28% (Table 5), showing a centimeter-level accuracy in virtual equipment placement. The quality of surface reconstruction is assessed using the distance between the reconstructed mesh and the original point cloud.⁽¹⁸⁾ Ninety percent of point cloud deviations were positioned below 1.5 cm. Such a consistency level indicates that the integration of laser scanning and photogrammetry data effectively reduces noise in raw scan data, providing a basis for subsequent IoT sensor integration.⁽²⁰⁾

The utility of the laboratory management system relies on the precision of the indoor positioning system (IPS). We employed a weighted trilateration algorithm based on *RSSI*, utilizing a signal attenuation model to estimate distances.⁽²¹⁾ The relationship between *RSSI* and distance (d) is defined as follows.

Table 5
Modeling accuracy comparing physical measurements and digital twin dimensions.

Measurement point	Actual dimension (mm)	Model dimension (mm)	Absolute error (mm)	Relative error
1 (wall length)	12540	12521	19	0.15%
2 (door width)	900	903	3	0.33%
3 (column height)	4500	4510	10	0.22%
4 (window width)	1800	1793	7	0.39%
5 (room width)	8640	8655	15	0.17%
6 (ceiling height)	3200	3208	8	0.25%
7 (workbench length)	2400	2389	11	0.46%
8 (corridor width)	1500	1506	6	0.40%
9 (partition height)	2100	2094	6	0.29%
10 (cabinet width)	1200	1207	7	0.58%
11 (beam width)	400	396	4	1.00%
12 (window height)	1500	1508	8	0.53%
13 (door height)	2100	2092	8	0.38%
14 (shelf length)	1800	1812	12	0.67%
15 (pillar width)	600	595	5	0.83%
16 (duct diameter)	320	323	3	0.94%
17 (floor thickness)	150	148	2	1.33%
18 (lab bench height)	850	857	7	0.82%
19 (storage area width)	3600	3588	12	0.33%
20 (equipment length)	856	862	6	0.70%
Average	—	—	8.2	0.28%

$$RSSI = -[10n\log_n(d) + A] \quad (2)$$

Here, A represents the $RSSI$ reference value at 1 m (calibrated at -58 dB) and n is the path-loss exponent (determined as 2.8). To evaluate IPS, a 10×10 m² grid with 25 test points was established. The results are shown in Table 6. The performance evaluation result of the BLE positioning system shows a significant correlation between environmental geometry and signal accuracy. In central open areas, where a dominant line-of-sight path is available, the framework showed an average error of 0.42 m and an 80th percentile error of 0.50 m. In contrast, obstructed zones containing metallic equipment and structural walls showed significant signal degradation due to multipath interference and shadowing, resulting in an average error of 0.89 m. Despite these variations, the overall 80th percentile error of 0.90 m supports the robustness of the framework for submeter asset tracking. The overall mean error of 0.71 m also indicates the effectiveness of the weighted trilateration algorithm in mitigating $RSSI$ noise, establishing the system as a viable solution for real-time laboratory resource management.

Figure 4 shows a heatmap of positioning errors in the laboratory environment. A wall corner and a metal cabinet are marked as grey rectangles. Errors increased in proximity to these obstructions due to multipath interference and signal shadowing. Areas farther from obstacles showed low errors (<0.5 m), whereas regions adjacent to the wall corner and cabinet showed higher errors (>1.5 m). In Fig. 4, the horizontal color bar provides a direct quantitative reference,

Table 6
Indoor positioning accuracy across different laboratory zones using RSSI-based weighted trilateration algorithm.

Test area	Number of test points	Average error (m)	Maximum error (m)	80th percentile error (m)
Central open area	9	0.42	0.85	0.5
Edge/obstructed area	16	0.89	2.15	1.2
Overall	25	0.71	2.15	0.9

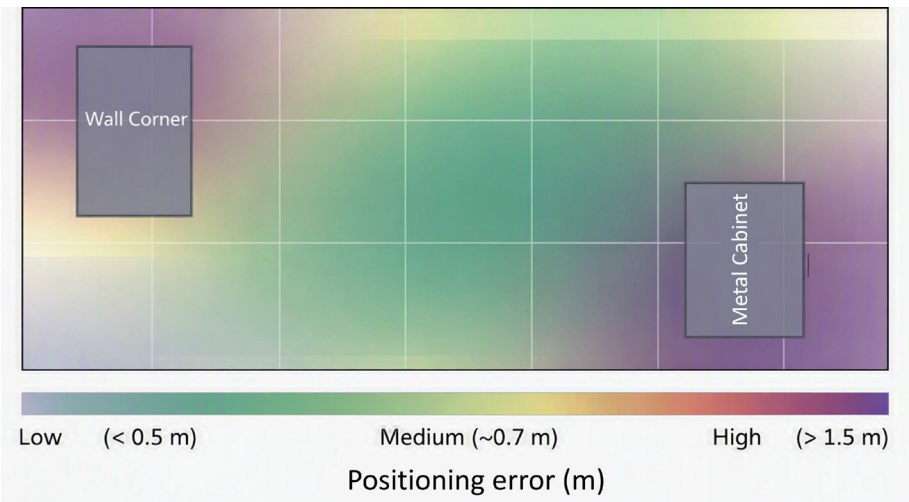


Fig. 4. (Color online) Heatmap illustrating spatial distribution of positioning errors. Higher deviations are observed in peripheral and obstructed areas due to multi-path interference.

ensuring that the visual tones correspond precisely to measured error values. These fluctuations are attributed to multipath interference and signal shadowing, phenomena commonly observed in dense laboratory environments.⁽¹²⁾ Nevertheless, the overall average error of 0.71 m remains well within the threshold required for reliably identifying specific workbenches or equipment zones.

The operational reliability of the system was evaluated across five modules, as detailed in Table 7. The architecture of the framework balanced high-fidelity visualization with low-latency data processing.⁽²²⁾ The 3D visualization module presented a response time of less than 200 ms, owing to the implementation of LOD switching, which optimizes the rendering load based on the user’s zoom level.⁽²²⁾ The high-density mesh generated by initial laser scanning did not impede the user experience during real-time navigation. The asset positioning and equipment monitoring modules show high practical utility. The position update latency was maintained under 3 s, which is sufficiently short for monitoring moving assets in the laboratory. The recognition accuracy for equipment status exceeded 98% for power state and 95% for vibration sensing, proving that the heterogeneous IoT sensor network reliably distinguished between active and idle states. The environmental monitoring module exhibited a robust alert mechanism with a push latency of less than 10 s, ensuring that safety-critical limit alerts reach administrators in

Table 7

Performance metrics and functional validation results for laboratory management modules.

Module	Test item	Result
3D visualization	Model loading, roaming, zooming, info queries	Smooth; normal LOD switching; response time < 200 ms
Asset positioning	Real-time position updates, trajectory playback	Position update latency < 3 s; smooth trajectory playback
Equipment monitoring	Status (on/off/running) recognition accuracy	Power judgment accuracy > 98%; vibration accuracy > 95%
Environmental monitoring	Real-time data display, limit alerts	Refresh cycle 1 min; alert push latency < 10 s
Equipment booking	Booking, approval, and conflict detection workflow	Process is smooth with no logical errors

near real time. These metrics showed that the framework meets the performance requirements for professional laboratory resource management.

To assess the framework's robustness under peak operational load, a stress test was conducted simulating 100 concurrent web users alongside 100 active sensor nodes reporting data at 10 s intervals. The results of this simulation are shown in Fig. 5, which tracks resource allocation over a continuous testing period.

The server's CPU utilization (the blue line) exhibited a stable trend, reaching a peak of approximately 65%. Despite the high volume of concurrent requests, the CPU usage fluctuated within a manageable range, suggesting that the backend logic efficiently handles parallel data streams. The memory consumption (represented by the green line) remained remarkably stable, plateauing at roughly 40%. This lack of significant memory drift indicates the absence of memory leaks and confirms the efficiency of the system's data buffering and storage management. The response time was maintained at shorter than 300 ms throughout the peak load phase. These metrics indicate that the developed framework handled the expected traffic of a large-scale academic department without significant latency or risk of system failure. By maintaining a 35% CPU overhead and 60% memory headroom, the framework proves its sufficient scalability to accommodate future expansions, such as the integration of additional sensor nodes or a larger user base.⁽²³⁾ The performance of the developed framework was evaluated by comparing operational metrics before and after system implementation. The comparative data, derived from a combination of backend server logs and structured user surveys, are summarized in Table 8.

The transition from manual to automated management resulted in a significant reduction in the number of time-intensive administrative tasks (Fig. 6). The average equipment finding time decreased by 86.7%, dropping from 15 to 2 min. This improvement is attributed to the real-time spatial positioning and 3D visualization, which enable users to navigate in an asset's coordinates. The equipment inventory time was reduced since the digital twin allows for remote inventory in the sensor network rather than requiring a presence for every item audit. Resource efficiency also improved

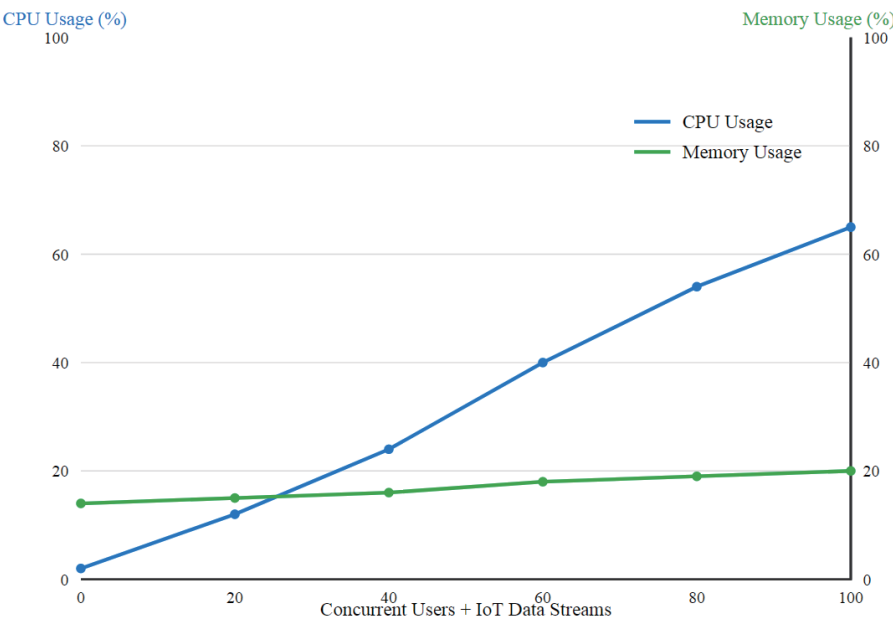


Fig. 5. (Color online) Server resource utilization profiles (CPU and memory) during high-concurrency stress testing with 100 simultaneous users and sensor nodes.

Table 8
Laboratory operational efficiency indicators before and after system implementation.

Indicator	Before application	After application	Change
Average equipment finding time	~15 min	~2 min	Reduced by 86.7%
Equipment inventory time	~4 person-days	~0.5 person-days (remote)	Reduced by 87.5%
Peak space utilization	~65%	~77%	Increased by 18.5%
Average equipment utilization	~30%	~42%	Increased by 40%
Energy waste (devices left on)	5–8 incidents per week	0–1 incidents per week	Significantly reduced

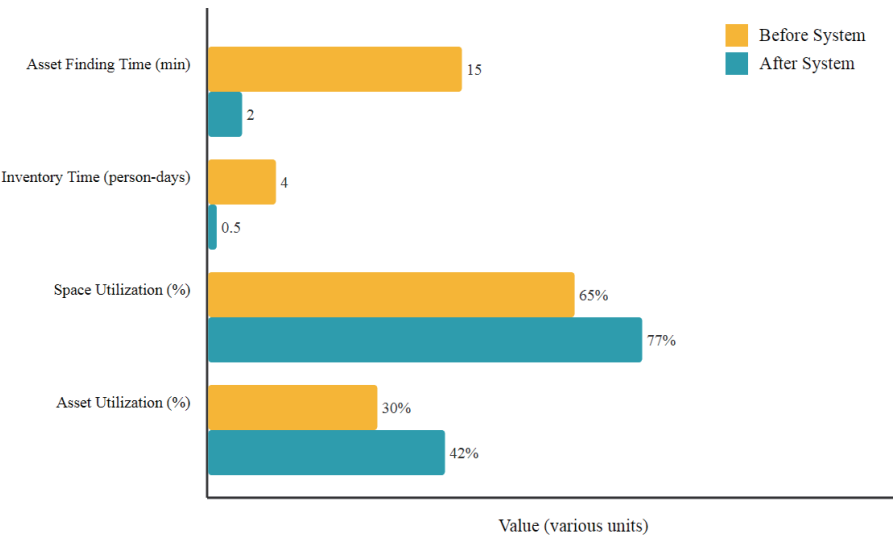


Fig. 6. (Color online) Comparison of performance indicators demonstrating improvements in equipment search time, inventory efficiency, and resource utilization.

markedly. The peak space utilization increased by 18.5% and average equipment utilization increased by 40%, indicating that data-driven scheduling and visibility help alleviate bottlenecks. Finally, the framework reduced the number of energy waste incidents from nearly one per day to almost zero, providing real-time alerts for equipment left active outside of laboratory hours.

4. Discussion

Sensor technology is vital in high-fidelity laboratory management, since the complexity of indoor environments necessitates robust sensor fusion algorithms. A heterogeneous sensor fusion framework can be applied to a challenging non-line-of-sight environment. The integration of 3D scanning with BLE and vibration sensors provides a methodology for mitigating the inherent noise of individual low-cost sensors. By employing the 3D spatial model as a geometric constraint, the accuracy of RSSI-based positioning was enhanced, achieving an overall 80th percentile error of 0.90 m. These results indicate that sensor performance in industrial and academic settings can be enhanced through hardware refinement and context-aware data fusion.⁽²⁰⁾ The high accuracy in equipment status recognition (98% for power and 95% for vibration) proves the effectiveness of a multimodal sensing network that combines electrical and mechanical signals to establish a more reliable ground truth of asset utilization than single-source sensing alone.⁽¹²⁾

Compared with existing laboratory management platforms, the developed framework has advantages in localization accuracy, operational monitoring depth, and workflow efficiency (Table 9). RFID and BLE contribute to saving search time, but they have errors ranging from 1.2 to 2.5 m in locating equipment on a 2D map. Building information modeling-building management system (BIM-BMS) platforms enable static visualization but they depend on manual updates or sensor data from fixed positions, which limits capturing equipment status and results in a moderate utilization degree. Vision-based monitoring methods improve positioning accuracy to 0.8–1.5 m, but they present occlusion in crowded laboratory layouts and can only record surface movement.

Table 9
Laboratory operational efficiency indicators before and after system implementation.

Method	Spatial visualization accuracy	Positioning accuracy	Equipment status monitoring	Operational efficiency gain
RFID/BLE ^(G1)	2D map only, no geometric fidelity	1.2–2.5 m	Location only	Search time reduction by 50%
BIM-BMS ^(G2)	Static BIM, geometric error < 10 mm	Not applicable (static asset tags)	Environmental parameters only	Moderate utilization gain
Vision-based monitoring ^(G3)	Camera-based, geometric error of 50–100 mm	0.8–1.5 m	Surface movement only	Occlusion-limited
Framework in this study	3D scan, spatial error of 8.2 mm	0.71 m (sub-meter)	98% (power) / 95% (vibration)	Search time reduction of 86.7%, space utilization rate increased by 18.5%

The developed framework shows higher precision by combining 3D laser-scanned point clouds with IoT sensing than conventional methods. Through spatial visualization, millimeter-level accuracy is obtained, and BLE positioning is stabilized at an average error of 0.71 m through *RSSI*-weighted trilateration. In equipment monitoring, recognition rates reached 98% for power states and 95% for vibration states using smart plugs and vibration sensors. These improvements result in measurable operational gains, including an 86.7% reduction in search time and an 18.5% increase in space utilization.

The effectiveness of the digital twin developed in this study relies on the reliability of the sensor layer. Without the high-precision point clouds generated by laser scanning, spatial visualization will lack the centimeter-level accuracy (8.2 mm average error) required for precise asset tracking. Sensor technology is essential in the framework, transforming a static 3D model into a digital twin. IoT sensors deliver real-time updates with a latency shorter than 10 s and enable the framework to transform from a descriptive visualization tool to a predictive management platform. These results also highlight a transition from reactive to proactive management.

Traditional laboratory management relies on retrospective audits, which are infrequent and error-prone. In contrast, 3D spatial data with real-time IoT sensors enable the establishment of a framework for automated laboratory management.⁽¹²⁾ Heatmaps generated by positioning sensors can be used for persistent queuing at 3D printers in one zone, whereas devices in another remain idle. By relocating equipment using the framework, workloads can be optimized. Status monitoring also reduces energy waste by alerting administrators to machines left active. These examples show how precise sensor data and spatial visualization allow administrators to optimize resources based on actual usage rather than intuition.

Despite these advances, the framework needs to be improved. Multipath interference and shadowing from dense metallic structures increased localization error to 2.15 m in the experiment. Spatial registration required periodic manual rescanning to reflect layout changes, adding operational overhead. High-resolution point clouds imposed heavy computational loads on client-side browsers without detailed optimization.⁽⁶⁾ To connect heterogeneous devices, dedicated protocols must be developed to reduce deployment complexity. The evaluation results of the developed framework in harsh conditions also showed limitations in conventional off-the-shelf sensors. To remove signal attenuation and multipath interference caused by dense metallic equipment, static BLE beacons require frequent calibration.

Therefore, self-calibrating sensors equipped with embedded MEMS and adaptive power management algorithms are required.⁽²⁴⁾ For non-intrusive vibration monitoring, battery-powered accelerometers can be replaced with flexible piezoelectric polymers and printable conductive carbon inks integrated directly into equipment housing for self-powered vibration sensing.⁽²⁵⁾ By integrating digital twin models with real-time sensor data, passive data collection can be advanced to cognitive sensing architectures, where sensors dynamically adjust sampling frequency and transmit power on the basis of real-time spatial conditions.⁽²⁶⁾

5. Conclusion

We developed an intelligent laboratory management framework by integrating 3D scanning in IoT sensor networks. High-precision digital twins with real-time positioning and environmental sensing capability were adopted, and space utilization was increased by 18.5%, asset search times were reduced by 86.7%, and non-operational energy waste was eliminated, compared with those before the implementation of the developed framework. A laboratory space and resource management framework with 3D scanning and IoT sensors was designed and implemented. By constructing a high-precision digital twin of the laboratory and deploying a multimodal IoT perception network, the framework enables the intuitive and intelligent management of space, assets, equipment status, and environmental conditions. The implementation results showed that the framework significantly improves management efficiency, resource utilization, and safety, providing a viable technical pathway to address long-standing limitations of traditional laboratory management.

The framework showed the effectiveness of sensor integration in complex non-line-of-sight indoor environments. By using the 3D spatial model (an average error of 8.2 mm) as a geometric constraint, the system stabilized *RSSI*-based positioning, achieving an 80th percentile error of 0.90 m. Complementary vibration and power sensors further enhanced accuracy, with recognition rates of 95 and 98%, respectively, establishing reliable asset utilization. These results highlight that sensor performance can be substantially improved not only through hardware refinement but also through context-aware data fusion strategies.

From a management perspective, the framework enables a transition from reactive to proactive management. Evaluation results showed that equipment search time was reduced from 15 to 2 min, and inventory tasks decreased from four person-days to just half a day. Real-time visibility provided by the digital twin leads to data-driven resource optimization, such as balancing workloads across zones and reducing energy waste through automated alerts. The synergy between precise spatial modeling and active IoT sensing fosters a significant evolution in facility management technology.

With high-precision spatial modeling, IoT sensor networks serve as an efficient and scalable solution for academic and research facilities. Sensor technology in intelligent laboratories enhances facility management practices. To extend the framework's capabilities from visualization to controllability and simulation, further research is required. For the remote operation of equipment using a 3D model, diverse control protocols must be integrated. Airflow and pollutant diffusion simulations must be conducted for the optimization of ventilation systems. By implementing a digital twin platform and self-calibrating MEMS sensors with self-powered flexible piezoelectric film monitors, environmental interference and mechanical noise can be accurately controlled during manufacturing and laser cutting. 3D spatial models also need to be integrated to mitigate signal degradation and develop adaptive sensors. To reduce multipath interference caused by dense metallic environments, mobile localization and mapping platforms and autonomous

algorithms must be integrated. Machine learning can also be used to identify resource needs and potential collaborators on the basis of historical usage patterns. VR tools add a layer for remote experiments and safety training. With such advanced technologies, the developed framework can further enhance the scalability and resilience of laboratory management in multi-floor facilities.

References

- 1 G. Marques and R. Pitarma: Appl. Sci. **9** (2019) 438. <https://doi.org/10.3390/app9030438>
- 2 S. Lee and M. Kim: J. Appl. Reliab. **19** (2019) 85. <https://doi.org/10.33162/jar.2019.03.19.1.85>
- 3 N. Telagam, S. Panda, N. Kandasamy, and M. Nanjundan: IJEAT **8** (2019) 2434. <https://www.ijeat.org/wp-content/uploads/papers/v8i5/E7336068519.pdf>
- 4 L. C. Tagliabue, F. Re Cecconi, S. Rinaldi, A. Flammini, and A. L. C. Ciribini: IOP Conf. Ser.: Earth Environ. Sci. **296** (2019) 012056. <https://doi.org/10.1088/1755-1315/296/1/012056>
- 5 J. Yao and Z. Yuan: Appl. Math. Nonlinear Sci. **10** (2025) 1. <http://archive.sciendo.com/AMNS/amns-2025-0124.open-issue/amns-2025-0124/amns-2025-0124.pdf>
- 6 J. S. Ortiz, V. H. Andaluz, and C. P. Carvajal: Sensors **26** (2026) 2023. <https://doi.org/10.3390/s26072023>
- 7 Z. Ma, Q. Zhou, J. Liu, R. An, T. Zhang, X. Chen, J. Dai, and Y. Geng: Electronics **15** (2026) 573. <https://doi.org/10.3390/electronics15030573>
- 8 K. Choutri, M. Lagha, S. Meshoul, H. Shaiba, A. Chegrani, and M. Yahiaoui: Sensors **24** (2024) 4121. <https://doi.org/10.3390/s24134121>
- 9 S. Li, X. Gao, W. Wang, and X. Zhang: J. Phys. Conf. Ser. **1549** (2020) 022107. <https://doi.org/10.1088/1742-6596/1549/2/022107>
- 10 M. Kowalski, D. Rybarczyk, and A. Milecki: Appl. Sci. **14** (2024) 11587. <https://doi.org/10.3390/app142411587>
- 11 A. Eccher, F. Pagni, M. Dominici, L. R. Bonetti, S. Marletta, E. Munari, G. Cazzaniga, A. V. Parwani, V. L'Imperio, and A. P. Dei Tos: Diagn. Pathol. **20** (2025) 84. <https://doi.org/10.1186/s13000-025-01679-2>
- 12 S. H. Abdhussain, B. M. Mahmmoud, A. Alwhelat, D. Shehada, Z. I. Shihab, H. J. Mohammed, T. H. Abdulameer, M. Alsabah, M. H. Fadel, S. K. Ali, G. H. Abbood, Z. A. Asker, and A. Hussain: Computers **14** (2025) 342. <https://doi.org/10.3390/computers14080342>
- 13 D. Jeong, J. Kim, S. Bae, and H. Jung: J. Korea Inst. Inf. Commun. Eng. **23** (2019) 2234. <https://doi.org/10.6109/jkiice.2019.23.1.90>
- 14 J. Zhong, C. Chen, Q. Zhang, and W. He: Mob. Inf. Syst. **2022** (2022) 1038526. <https://doi.org/10.1155/2022/1038526>
- 15 A. S. Borkowski and A. Kubrat: ENG **5** (2024) 2395. <https://doi.org/10.3390/eng5040125>
- 16 M. Beykou, V. Bousgouni, N. Moser, P. Georgiou, and C. Bakal: Biosens. Bioelectron. **262** (2024) 116513. <https://doi.org/10.1016/j.bios.2024.116513>
- 17 A. Cetinkaya, S. Irem Kaya, and S. A. Ozkan: Anal. Chim. Acta. **1357** (2025) 344080. <https://doi.org/10.1016/J.ACA.2025.344080>
- 18 E. Kapogianni and M. Sakellariou: Sensors **25** (2025) 1450. <https://doi.org/10.3390/S25051450>
- 19 R. Porras, B. Mobaraki, Z. Liu, T. Muñoz, F. Lozano, and J. A. Lozano: App. Sci. **15** (2025) 8701. <https://doi.org/10.3390/AP15158701>
- 20 S. SU, A. Nassehi, B. Hicks, and J. Ross: J. Manuf. Syst. **71** (2023) 224. <https://doi.org/10.1016/j.jmsy.2023.09.004>
- 21 K. Davoudian, L. Nemtsov, and M. Thompson: Front. Sens. **6** (2025) 1641221. <https://doi.org/10.3389/FSENS.2025.1641221>
- 22 T. Matsumoto, M. Suzuki, M. Yamaguchi, M. Aoki, S. Konagai, and K. Murasaki: <https://arxiv.org/html/2508.15398v1> (accessed April 2026).
- 23 B. Liu, Y. Zhou, H. Fu, P. Fu, and L. Feng: Sensors **22** (2022) 4315. <https://doi.org/10.3390/s22124315>
- 24 Y. Chen, X. Zhang, and C. Lu: Chem. Sci. **15** (2024) 16436. <https://doi.org/10.1039/d4sc05166a>
- 25 E. Nica, G.H. Popescu, M. Poliak, T. Klietk, and O.-M. Sabie: Mathematics **11** (2023) 1981. <https://doi.org/10.3390/math11091981>