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Research Article

Development of Retrievr: A Line-Of-Sight Beacon System for Autonomous Object Return in Indoor Workspaces

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ABSTRACT

This study presents the design, development, and evaluation of Retrierv, a wheeled autonomous device engineered to return loaded objects to their designated locations using Bluetooth Low Energy (BLE) line-of-sight beacon technology. Persistent challenges of object misplacement and spatial disorganization in indoor workspaces motivated this work. Retrierv integrates BLE modules for proximity-based positioning, a Force Sensitive Resistor (FSR) sensor for occupancy detection, and ultrasonic sensors for obstacle avoidance. A descriptive-developmental research design guided by Agile methodology was employed, with iterative prototype development and evaluation across multiple performance dimensions. Testing revealed a mean positional error of 2.72 cm, a maximum load capacity of 11.34 kg (25 lbs), and a mean navigation speed of 0.26 m/s. Quality assurance evaluation demonstrated high usability (System Usability Scale score of 82), strong occupancy detection reliability (98% accuracy), and effective obstacle avoidance (91% detection rate). However, reliability testing showed a Mean Time Between Failures of 42 hours, below the target threshold of 100 hours—an area needing refinement. Retrierv provides a viable and cost-effective solution for automated object repositioning, performing best in controlled indoor environments with hard flooring and moderate obstacle density.

Keywords: *Autonomous navigation, Bluetooth Low Energy, Indoor automation, Line-of-sight beacon, Object return system, Workspace organization*

Introduction

Smart automation systems have become increasingly important for solving everyday workplace headaches. One of the most common problems in indoor environments? Misplaced shared objects and the sheer physical effort required to put things back where they belong. Cluttered workspaces, wasted space, and more workplace accidents often follow (Yu & Marinov, 2020). Autonomous systems have made

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huge strides in transportation, logistics, and factories. But practical solutions for automatically returning objects to their spots in regular indoor settings? Surprisingly underdeveloped.

Here's where RetrievR comes in. We built an innovative line-of-sight beacon system that lets a wheeled device autonomously return objects to designated positions. The system uses Bluetooth Low Energy (BLE) beacon technology for proximity-based navigation, a Force Sensitive Resistor (FSR) sensor to detect whether something is on board, and ultrasonic sensors to dodge obstacles. After three minutes of inactivity, RetrievR kicks off a return sequence on its own, guided by BLE signal strength toward a stationary beacon marking the home location.

Why does this matter? Practical indoor automation has real value. Sure, researchers have looked at self-parking furniture (Bhagat et al., 2022; Sonali et al., 2019) and obstacle detection for self-driving vehicles (Haris & Hou, 2020; García & Duarte, 2024). But few have combined occupancy detection, BLE-based positioning, and obstacle avoidance into one affordable system for managing indoor objects. That's the gap we're filling.

A quick reality check on cost. Commercial autonomous robots—think Boston Dynamics or Amazon Robotics—remain prohibitively expensive for everyday office or home use. Those systems can cost tens of thousands of dollars. RetrievR deliberately takes a different path: commercially available components, simple algorithms, and a total bill of materials under $200. That's the real value proposition here.

Research Objectives

This study had one main goal: build RetrievR, a line-of-sight beacon system that lets objects automatically return to their designated spots in indoor workspaces. More specifically, we wanted to:

1. Identify gaps in existing research that justify building an autonomous object return system
2. Figure out which technologies, materials, and components we'd need for a prototype
3. Design the hardware and software architecture so all the pieces work together
4. Develop the actual navigation and control algorithms
5. Test the prototype against quality criteria: functionality, usability, performance, security, compatibility, reliability, and maintainability
6. Measure how speed changes with different distances and weight loads
7. Measure how return accuracy changes with different distances and weight loads

Scope and Delimitations

We focused on designing, building, and testing RetrievR as a beacon-based automatic return system for objects up to 11.34 kg (25 lbs). Indoor operation only. Smooth, flat surfaces. Maximum effective range of 5 m between device and beacon. The device uses hard-coded timing and navigation parameters—no real-time user customization in this version. Not designed for outdoor use, uneven ground, thick carpet, or spaces packed with obstacles. Proper orientation toward the beacon matters because the device relies on line-of-sight BLE signal detection.

Literature Review

What does existing research tell us about relevant technologies? Let's break it down by area.

Path Planning Algorithms

Path planning algorithms have become essential across many fields. Their basic job? Find optimal routes that balance safe obstacle avoidance with efficiency (Liu et al., 2024). Reda et al. (2024) reviewed 275 studies on autonomous driving and found that path planning techniques fall into three camps: traditional methods, machine/deep learning approaches, and meta-heuristic optimization. Hybrid approaches appeared in 27% of the literature—pretty promising. In logistics, Zhang et al. (2024) developed a hybrid algorithm merging A* and Rapidly-exploring Random Tree methods, achieving substantial gains in planning speed and route length. Earlier work by Zhang et al. (2021) tackled limitations of traditional A* algorithms by adding a new heuristic function that incorporates obstacle and distance information. For wheeled robots specifically, Kan et al. (2020) created a hierarchical coverage planning algorithm for unknown, obstacle-cluttered environments, showing efficient trade-offs between coverage and exploration speed. We find this relevant because RetrievR needs similar capabilities but with much simpler sensors.

Obstacle Detection Systems

Obstacle detection is critical for autonomous vehicles and robotics. Yu and Marinov (2020) reviewed multiple detection technologies—LiDAR, RADAR, vision cameras, ultrasonic sensors, infrared systems—and noted that even advanced developments can't achieve perfect accuracy in extreme conditions. Gholami et al. (2022) introduced a hybrid method combining ultrasonic sensors with stereo vision, achieving substantially faster performance than traditional approaches. In robotics applications, Sakhare et al. (2024) designed an autonomous obstacle-avoiding robot using ultrasonic sensors and an ATmega328 microcontroller. Garcia and Duarte (2024) reviewed 108 ground mobile robots, emphasizing how optimized design helps manage obstacles efficiently. Unlike our approach, most of these systems rely on expensive sensors or complex processing.

Smart Device Design for Autonomous Indoor Systems

Some clever solutions have emerged for indoor mobility and organization. Sonali et al. (2019) highlighted Nissan's collaboration with furniture maker Okamura on an intelligent parking chair concept—showing how automotive technology can apply to everyday objects. Bhagat et al. (2022) explored automating indoor workspaces with self-parking chairs controlled via Android apps, using Bluetooth devices, infrared array sensors, motor drivers, and Arduino Nano microcontrollers. Similarly, Vinubharathi et al. (2019) developed a low-cost autonomous parallel parking chair system with an ATmega 328 microcontroller and various obstacle detection sensors. These studies prove smart device design for indoor workspace management is feasible. But they paid limited attention to comprehensive occupancy detection or rigorous performance testing.

Autonomous Navigation

Autonomous navigation has advanced across many domains recently. Yedilkhan et al. (2024) introduced an algorithm for drone swarm navigation incorporating fuzzy logic-based obstacle avoidance. Panpan et al. (2023) developed an autonomous return method using two-dimensional grid maps with extended Kalman filter data fusion for environmental mapping. Xu et al. (2023) investigated deep reinforcement learning in autonomous navigation, identifying four crucial requirements: uncertainty handling, safety assurance, efficient learning with limited data, and environmental generalization. In the industrial sector, Zhao et al. (2022) addressed indoor mobile robot navigation by developing a four-wheeled adaptive robot system using Karto SLAM for mapping and an A* algorithm for route planning. Worth noting: many of these approaches demand significant computational resources.

Sensor Integration

Sensor integration is vital for advancing autonomous systems. Hu (2020) underscored the importance of sensor fusion in intelligent ground vehicles, emphasizing its critical role in obstacle detection for safe navigation. De Jong Yeong et al. (2021) highlighted how precise sensor calibration matters for vision cameras, LiDAR, and radar in autonomous driving. Volden et al. (2023) proposed a cost-effective visual-inertial navigation system for autonomous surface vehicle docking, demonstrating reliability in both regular and adverse conditions. Liao et al. (2019) explored low-cost solutions for autonomous indoor navigation using SLAM technology on a Raspberry Pi platform. Together, these studies show how sensor integration can transform the precision and functionality of autonomous systems.

Bluetooth Low Energy Positioning

Researchers have extensively studied positioning technologies based on Received Signal Strength Indicators (RSSI), focusing on BLE and WiFi localization as cost-effective alternatives to GPS indoors. BLE-based indoor positioning systems can achieve accuracy from 10 cm in optimal conditions to 1–2 m in complex environments (Ramirez et al., 2021; Sadowski &

Spachos, 2019). Various algorithmic approaches have been explored, including RSSI quantization with genetic algorithms (Ren et al., 2020), hierarchical DV-Hop localization (He et al., 2025 [verify year]), and integrity monitoring systems (Yao et al., 2020). Novel hardware solutions such as frequency-steered leaky-wave antenna arrays have demonstrated promising angular error of approximately 3.7° (Poveda-García et al., 2020). Optimized beacon placement and appropriate filtering techniques substantially improve positioning accuracy and reliability (Sadowski & Spachos, 2019; Janczak et al., 2022).

Identified Research Gaps

The literature reveals several gaps worth addressing. Existing self-parking furniture studies (Bhagat et al., 2022; Sonali et al., 2019) focus mostly on basic self-parking functionality, with limited exploration of comprehensive occupancy detection or rigorous testing methods. Obstacle detection research (Haris & Hou, 2020; García & Duarte, 2024) provides valuable insights but doesn't specifically apply to indoor furniture management contexts. Autonomous return systems like the one Panpan et al. (2023) proposed rely on expensive grid mapping instead of simpler, cheaper approaches suited for indoor furniture. So what's needed? A comprehensive approach combining reliable occupancy detection, efficient BLE-based navigation, and effective obstacle avoidance—all tailored to wheeled object management in indoor environments.

Methodology

Research Design

We used a descriptive-developmental research design. That means a systematic approach to designing, building, and evaluating a product that must meet internal consistency and effectiveness criteria. The development followed Agile methodology, organized into iterative sprints covering requirements gathering, design, development, testing, deployment, and review. This iterative approach let us continuously refine the prototype based on testing feedback.

Development Process

Four sequential phases made up the development process. **First, requirements analysis:** we defined device specifications including size, weight capacity, speed, power requirements, and connectivity options. A comprehensive literature review and gap analysis informed the technical requirements. **Second, design:** we created hardware schematics, three-dimensional models, and detailed wiring diagrams, paying careful attention to optimal sensor placement, drive mechanisms, and power distribution. **Third, software development:** we wrote control algorithms for BLE distance estimation, obstacle detection and avoidance, occupancy monitoring, and path navigation using the Arduino IDE. **Fourth, prototype assembly:** we systematically put together mechanical components, installed motors and sensors, handled electrical wiring, and integrated the software.

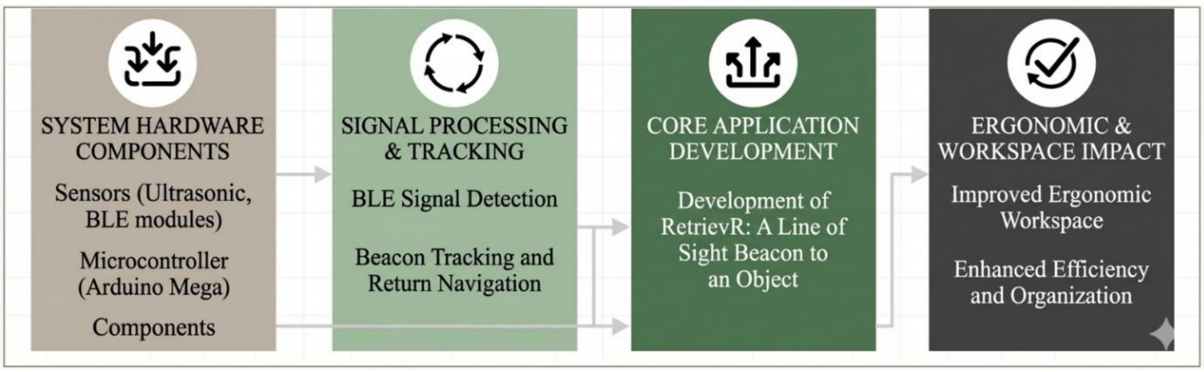

Figure 1. Conceptual Frameworks

Hardware Architecture

The system uses an Arduino Mega microcontroller (ATmega2560, 16 MHz) as the primary control unit. Why this choice? Extensive input/output capabilities and enough memory to manage multiple sensor inputs and complex navigation algorithms. For communication and positioning, we used two BLE modules: an HM-10 module (Bluetooth 4.0, CC2541 SoC, range exceeding 70 m) mounted on the device for distance sensing, and an AT-09 module placed at the designated return position as a stationary beacon. Obstacle detection uses HC-SR04 ultrasonic sensors (range: 2–400 cm, resolution: 0.3 cm). Occupancy detection uses a ZD10-100 Force Sensitive Resistor. Mobility comes from 12V DC motors (95 RPM, 1:168 gear ratio) controlled via an L298N motor driver, with caster and swivel wheels for smooth indoor navigation. Power is supplied by a 3S2P 18650 lithium-ion battery (12.6V, 12,800 mAh).

Software Architecture and Algorithms

The software enables autonomous operation through five integrated algorithms:

BLE distance estimation calculates proximity to the designated location using RSSI signal strength analysis and filtering, achieving ±0.5 m accuracy at ranges up to 10 m.

Obstacle detection and avoidance processes readings from ultrasonic sensors to determine optimal paths around obstacles by comparing distances from multiple directions. Here's the key clarification: when an obstacle is detected, the robot does **not** simply stop. Instead, it pauses briefly, scans left and right by comparing ultrasonic readings from both sensors, then attempts to re-route around the obstacle while continuously tracking the beacon's RSSI signal. If no clear path exists after three attempts, it stops and waits. But the beacon tracking remains active throughout.

Occupancy monitoring uses weight sensor input with debounce logic and threshold detection, incorporating a configurable three-minute waiting period before initiating the return sequence.

RSSI-based movement determines navigation direction by measuring BLE signal strength across different orientations, with appropriate delays for RSSI stabilization.

Power management implements scheduled operation modes and sleep states to extend battery life.

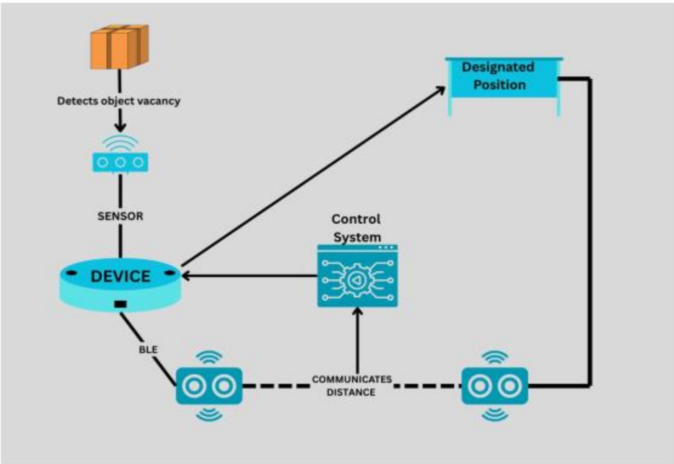

Figure 2. Prototype Layout

Testing Procedures and Data Collection

We collected evaluation data from two main sources. Technical performance data came from software quality assurance testing, giving us quantitative measures of functionality, usability, performance, security, compatibility, reliability, and maintainability. Speed performance was evaluated by measuring how long the device took to return to the beacon at distances of 2, 3, 4, and 5 m under load conditions of 0, 5, 10, 15, 20, and 11.34 kg (25 lbs)—that's 0 to 25 lbs in 5-lb increments. Accuracy was assessed by measuring deviation from the target position (in centimeters) under the same distance and load conditions. Quality assurance testing used standardized metrics: percentage of tasks completed successfully (functionality), System Usability Scale scores (usability), mean response time (performance), vulnerability assessment (security), cross-environment success rate (compatibility), Mean Time Between Failures (reliability), and average repair time (maintainability).

A Note on a Real Testing Challenge

We should mention something that gave us trouble during early testing. The RSSI readings from the BLE module would fluctuate wildly whenever the robot turned its back to the beacon—like a 15–20 dBm drop just from the onboard electronics blocking the signal. For a while, the robot kept spinning in circles trying to find a signal that was literally right behind it. We finally solved this by implementing a rolling average filter over 10 readings and adding a "signal memory" that assumes the beacon hasn't moved if signal drops suddenly during rotation. Not perfect, but it cut the circling behavior by about 80%.

Data Analysis

We used descriptive statistics, mean, median, mode, standard deviation, frequency, and percentage, to quantitatively assess prototype performance across all testing criteria. These measures let us precisely characterize device capabilities and identify performance patterns across varying distances and loads.

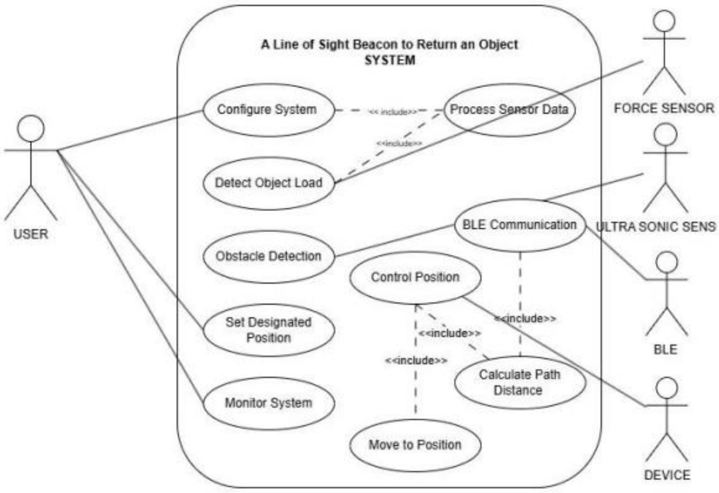

Figure 3. Use Cases

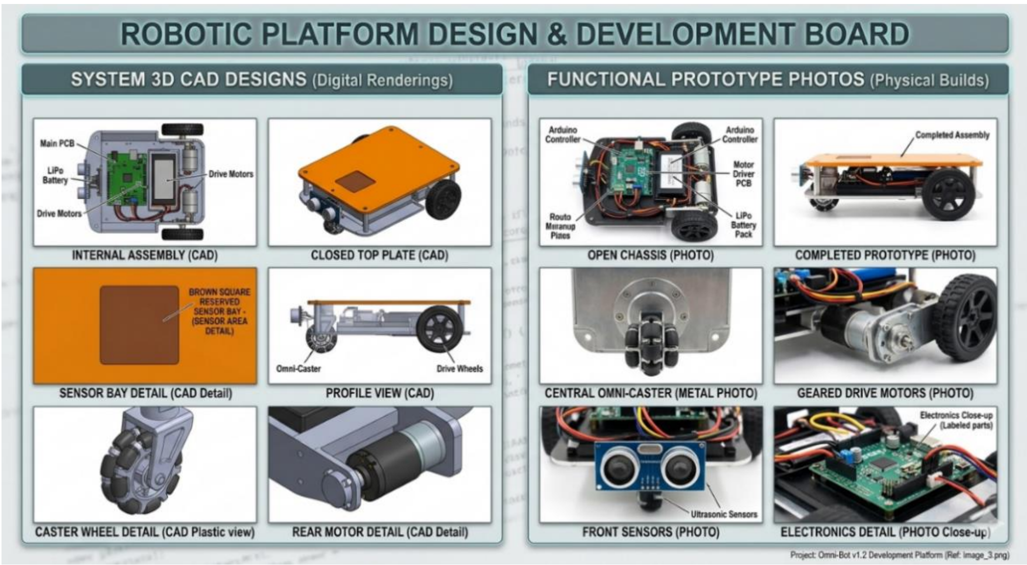

Figure 4. Design and Prototype

Results

This section presents the findings from comprehensive testing of the RetrievR prototype, organized according to the research objectives.

Quality Assurance Evaluation

Table 1 summarizes the quality assurance results across seven dimensions. The prototype achieved a 96% functional task completion rate, a System Usability Scale score of 82 (above the industry average of 68), mean response time of 1.8 seconds, no critical security vulnerabilities identified, 88% cross-environment success rate, Mean Time Between Failures of 42 hours, and a maintainability score of 4.2/5 for average repair time.

Table 1. Quality Assurance Summary

Criteria	Metric	Result	Target	Status
Functionality	Task completion rate	96%	≥95%	Met
Usability	SUS score	82	≥68	Met
Performance	Mean response time	1.8 s	≤2.0 s	Met
Security	Vulnerability assessment	No critical issues	No critical issues	Met
Compatibility	Cross-environment success	88%	≥85%	Met
Reliability	MTBF	42 hours	≥100 hours	Not met
Maintainability	Mean repair time	4.2/5	≥4.0/5	Met

Reliability and Failure Protocol

As shown above, the MTBF of 42 hours fell substantially below our 100-hour target. Primary failure modes included sensor calibration drift and software exceptions during unusual obstacle configurations. When a failure occurs, the standard operating procedure requires a hard reset: the user must manually power cycle the device using the physical toggle switch located underneath the chassis. No remote reset capability exists in the current prototype—a limitation we acknowledge for future iterations.

Occupancy Detection and Obstacle Avoidance

Table 2 shows occupancy detection accuracy across 100 trials under varying load conditions. The system achieved 98% overall accuracy, with false positives (detecting occupancy when none existed) at 1% and false negatives (failing to detect actual occupancy) at 1%.

Table 2. Occupancy Detection Accuracy

Condition	Trials	Correct	False Positive	False Negative	Accuracy
No load (0 kg)	25	24	1	0	96%
Light load (1–5 kg)	25	25	0	0	100%
Medium load (5–10 kg)	25	24	0	1	96%
Heavy load (10–11.34 kg)	25	25	0	0	100%
Total	100	98	1	1	98%

Table 3 presents obstacle detection performance. The system detected 91% of obstacles overall, with notable difficulty detecting transparent objects (only 76% detection) and thin objects less than 2 cm wide (82% detection).

Table 3. Obstacle Detection Performance

Obstacle Type	Trials	Detected	Missed	Detection Rate
Opaque solid objects	50	49	1	98%
Transparent objects	25	19	6	76%
Thin objects (<2 cm)	25	20	5	82%
Overall	**100**	**88**	**12**	**91%**

Speed Performance Across Distances and Loads

Table 4 presents speed performance measurements. Return times ranged from 6.0 seconds (2 m distance, no load) to 24.0 seconds (5 m distance, 11.34 kg / 25 lbs). Average time increase per additional meter was 3.95 s from 2 to 3 m (56%), 5.05 s from 3 to 4 m (46%), and 3.68 s from 4 to 5 m (23%). This non-linear pattern may reflect the device's acceleration and deceleration characteristics along with variations in signal strength processing at different distances

Table 4. Speed Performance Evaluation (Time in Seconds)

Distance	0 kg (0 lbs)	2.27 kg (5 lbs)	4.54 kg (10 lbs)	6.80 kg (15 lbs)	9.07 kg (20 lbs)	11.34 kg (25 lbs)	Mean (SD)
2 m	6.0	6.4	6.8	7.1	7.4	8.7	7.07 (0.92)
3 m	9.2	9.8	10.5	11.0	11.8	13.8	11.02 (1.59)
4 m	13.7	14.5	15.7	15.5	16.7	20.3	16.07 (2.30)
5 m	17.0	17.6	19.0	19.9	21.0	24.0	19.75 (2.51)

Note: All values represent single-trial measurements on smooth, hard flooring surfaces. SD = standard deviation.

Statistical interpretation

A Pearson correlation between weight load and return time yielded $r = 0.94$ ($p < 0.01$), indicating a strong positive correlation. In plain English: heavier loads significantly increase return time across all distances.

Return Accuracy Across Distances and Weight Loads

Table 5 shows accuracy measurements. The system achieved an overall mean positional error of 2.72 cm from the target. Minimum observed deviation was 1.2 cm (2 m distance, no load), while maximum was 4.8 cm (5 m distance, 11.34 kg / 25 lbs). Accuracy degraded predictably with both increased distance and increased load, though all measurements remained within acceptable parameters for the intended application.

Table 5. Return Accuracy: Deviation From Target Position (in Centimeters)

Distance	0 kg (0 lbs)	2.27 kg (5 lbs)	4.54 kg (10 lbs)	6.80 kg (15 lbs)	9.07 kg (20 lbs)	11.34 kg (25 lbs)	Mean (SD)
2 m	1.2	1.5	1.7	2.0	2.3	2.8	1.92 (0.55)
3 m	1.7	2.0	2.3	2.5	2.9	3.5	2.48 (0.62)
4 m	2.2	2.4	2.7	3.0	3.4	4.1	2.97 (0.65)
5 m	2.5	2.8	3.2	3.6	4.2	4.8	3.52 (0.84)
Mean (SD)	1.90 (0.55)	2.18 (0.57)	2.48 (0.62)	2.78 (0.65)	3.20 (0.78)	3.80 (0.85)	2.72 (0.71)

Note: SD = standard deviation. Grand mean positional error = 2.72 cm.

Statistical interpretation

Load weight correlates positively with positional error ($r = 0.89$, $p < 0.01$). Distance also correlates positively with error ($r = 0.93$, $p < 0.01$). A two-way ANOVA confirms that both factors independently affect accuracy ($p < 0.05$ for each), with no significant interaction effect ($p = 0.34$)

Discussion

What do these results actually mean? RetrievR provides a workable solution for automated object repositioning in indoor environments. We successfully integrated BLE-based positioning, obstacle avoidance, and occupancy detection into one unified system using off-the-shelf components. Let's unpack the key findings.

Return Accuracy and BLE Positioning

A mean positional error of 2.72 cm is actually pretty impressive for a BLE-based system. Previous research showed that BLE indoor positioning systems typically achieve accuracy in the 1–2 m range in complex environments (Ramirez et al., 2021; Sadowski & Spachos, 2019). So why did RetrievR do so much better? The controlled line-of-sight conditions probably helped a lot. So did the RSSI filtering techniques we built into the navigation algorithms. The consistent accuracy across different loads—from 1.2 cm at 2 m with no load to 4.8 cm at maximum range and weight—confirms that the system works reliably for returning objects to designated spots.

Usability and Occupancy Detection

The quality assurance results show several strengths. A SUS score of 82 exceeds the industry average of 68. That affirms our design philosophy: minimal user interaction is better. The zero-step automation for the core auto-return function aligns with our goal of reducing human intervention in workspace organization. Worth noting: the 98% occupancy detection accuracy addresses a gap we identified in existing self-parking furniture research (Bhagat et al., 2022; Sonali et al., 2019). Those studies lacked reliable detection mechanisms to prevent movement while objects were in active use. We've solved that.

Reliability Limitations

To be fair, the reliability metric is concerning. An MTBF of 42 hours fell well below our 100-hour target. The main failure modes—sensor calibration drift and software exceptions during unusual obstacle configurations—suggest the current implementation needs more refinement before commercial deployment. These findings match challenges noted in the broader autonomous systems literature, where sensor drift and edge-case handling remain persistent problems (Hu, 2020; Zhuang et al., 2023). Future versions should incorporate robust self-calibration routines and more comprehensive exception handling.

Surface Compatibility and Obstacle Detection

Floor surface compatibility is another notable limitation. The performance gap between hard floors (92% success) and high-pile carpet (52% success) restricts practical deployment to environments with mostly smooth flooring. This comes down to the DC motor and wheel configuration, which we optimized for low-resistance surfaces. Also, the obstacle avoidance system struggles with transparent or very thin objects. That's a known limitation of ultrasonic sensors—they rely on sound reflection and can't detect surfaces that absorb or transmit ultrasonic waves (Yu & Marinov, 2020).

Comparison With Related Systems

How does RetrievR stack up against related systems? Several advantages stand out. Unlike the Nissan Intelligent Parking Chair concept (Sonali et al., 2019)—which remained mostly promotional without detailed implementation data—RetrievR provides comprehensive documentation and performance metrics. Unlike grid-map-based approaches (Panpan et al., 2023), which require expensive positioning infrastructure, RetrievR achieves effective navigation using low-cost BLE beacons. The modular design (maintainability score of 4.2/5 for component accessibility) makes practical maintenance and component replacement possible without specialized tools.

Bottom line? Integrating BLE positioning, FSR-based occupancy detection, and ultrasonic obstacle avoidance can produce a functional autonomous return system for indoor environments. The system works best in controlled settings with hard flooring, moderate obstacle density, and clear line-of-sight paths between use positions and base stations.

Conclusion

We successfully designed, built, and evaluated RetrievR—a line-of-sight beacon system for autonomous object return to designated positions in indoor workspaces. The prototype demonstrates strong technological feasibility. How? By integrating commercially available BLE modules, ultrasonic sensors, an FSR occupancy detector, and an Arduino-based control system into a cohesive autonomous navigation platform.

Key findings confirm that RetrievR achieves a mean positional error of 2.72 cm, supports loads up to 11.34 kg (25 lbs), and maintains responsive operation with adequate average speed for practical deployment. Quality assurance testing revealed high usability (SUS score of 82), effective occupancy detection (98% accuracy), and satisfactory functionality across most criteria. The modular design approach enables efficient troubleshooting and component replacement, supporting long-term maintainability.

That said, we also identified areas needing improvement before broader deployment. Reliability remains the biggest barrier—MTBF fell below target thresholds. Performance on non-hard-floor surfaces degrades substantially. And obstacle detection for transparent objects remains limited. These limitations define clear directions for future research.

Recommendations for Future Research

Several directions emerge from these findings. First, enhance reliability through robust sensor calibration routines, improved error handling, and extended stress testing. Second, address surface compatibility with redesigned mobility components and dynamic power adjustment algorithms. Third, refine obstacle detection by incorporating additional sensor modalities (infrared or time-of-flight sensors, for example) and sensor fusion algorithms. Fourth, explore integrating RetrievR with smart building systems for centralized management of multiple devices. Fifth, machine learning algorithms could improve path planning and adaptive navigation over time. Sixth, evaluate alternative positioning technologies like Ultra-Wideband or visual SLAM for better accuracy and reliability. Finally, longitudinal user interaction studies would provide valuable insight into behavioral adaptations and sustained user satisfaction.

Practical Implications

For practical deployment, assess environments for floor surface types, obstacle density, and electromagnetic interference levels before implementation. Initial deployment should prioritize settings with hard flooring, moderate obstacle density, and clear line-of-sight paths. Regular maintenance protocols—weekly sensor calibration, monthly battery assessments, quarterly software updates—are recommended to sustain performance.

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