# GARDEN WATCH: A FRAMEWORK FOR NON-INTRUSIVE BEHAVIORAL MONITORING OF ELDERLY THROUGH ZOOMORPHIC DESIGN

ANHAR RISNUMAWAN[1,5], ACHMAD FAHRUL AJI[2,6], QINGWEI SONG[3], AND NAOYUKI KUBOTA[4]

[1,2,3,4]Department of Mechanical Systems Engineering, Graduate School of Systems Design, Tokyo Metropolitan University
6-6 Asahigaoka, Hino, Tokyo 191-0065, Japan
[5]Mechatronics Engineering Division, Politeknik Elektronika Negeri Surabaya, Indonesia
[6] Department of Electrical Engineering, Politeknik Negeri Semarang, Indonesia
e-mail: {[1]risnumawan-anhar, [2]achmad-aji, [3]qingwei-song}@ed.tmu.ac.jp, [4]kubota@tmu.ac.jp

**Abstract**

**Conventional health monitoring technologies for elderly populations face significant adoption barriers including clinical appearance, usability challenges, and stigmatization. Garden Watch addresses these obstacles through an open-source framework that embeds monitoring capabilities within a decorative steel owl garden statue. By leveraging the therapeutic context of home gardening where elderly engage in planting, watering, and nurturing living plants, our system transforms health monitoring into an aesthetically pleasing experience. The ESP32-C3-based implementation uses privacy-preserving sensors to establish personalized behavioral baselines while the owl's mechanical features (nodding, audio, vibration) serve dual purposes by providing plant care reminders for watering schedules and seasonal plantings while performing unobtrusive wellness checks. Experimental results confirm the system's ability to detect meaningful behavioral changes while maintaining a non-clinical appearance. This zoomorphic approach integrates monitoring technology into garden environments where older adults find purpose and joy, aiming to preserve dignity and autonomy while providing health insights that may support independent living among elderly gardening enthusiasts.**

**Keywords**

**Therapeutic Gardening; Elderly Health Monitoring; Zoomorphic Design; Ambient Assisted Living; Non-Intrusive Sensing.**

## 1. Introduction

The aging population strains healthcare systems worldwide, necessitating effective monitoring solutions for independent elderly living that respect autonomy [1]. Conventional technologies face adoption barriers due to clinical aesthetics, usability issues, privacy concerns, cost, and stigma [2], [3], with complex interfaces, perceived surveillance implications, and privacy fears significantly reducing acceptance among elderly populations [4].

Fig. 1. Garden Watch fits into an indoor gardening setting, its owl design blending zoomorphic aesthetics with decorative and unobtrusive monitoring roles for elderly users.

Therapeutic gardening, beneficial for physical, cognitive, and emotional health in older adults [5], provides an unobtrusive setting for monitoring. Ambient systems can detect behavioral shifts 11 days before health events, supporting early intervention [6], [7]. Long-term observational work has demonstrated that continuous monitoring can document deviations in activities that correlate with cognitive decline, frailty, and increased hospitalization risk [8].

Studies have demonstrated the efficacy of establishing personalized baselines for detecting health changes, achieving high accuracy (area under the ROC curve of 0.97) in predicting transitions to higher care levels [9]. However, conventional monitoring systems typically appear clinical and institutional, creating resistance among users who fear being labeled as "frail" or dependent [10]. Research shows that sensor-integrated companion systems can effectively monitor the elderly while offering a human-friendly appearance that supports aging-in-place, avoiding clinical aesthetics [11]. Additionally, advanced behavior estimation with fuzzy inference-based neural networks can accurately interpret complex daily activity patterns while ensuring dignity and privacy [12]. This framework embeds monitoring in a steel owl statue, leveraging zoomorphic design to reduce stigma and enhance acceptance [13], [14].

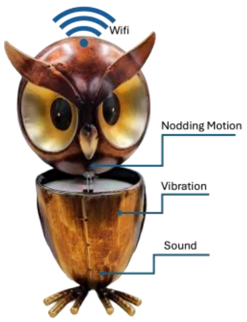


Fig. 2. Garden Watch blends into an indoor gardening setting, its owl-shaped design merging zoomorphic aesthetics with decorative and unobtrusive monitoring functions for elderly users.

This research addresses these challenges by developing Garden Watch, as shown in Fig. 1, an innovative monitoring framework embedded within a decorative garden element, specifically a steel owl statue positioned among potted herbs and flowering plants. Guided by the OWL (Organizing Well-being for Life) framework, which integrates health monitoring technologies into familiar everyday environments to support elderly independence while preserving dignity, Garden Watch transforms health monitoring from a clinical activity into a natural extension of therapeutic gardening practices. By incorporating a separate detection module that uses low-resolution thermal (AMG8833, 8×8) and depth (VL53L5X, 8×8) sensors, we create a privacy-preserving monitoring system that works alongside an aesthetically pleasing garden ornament. This approach maintains complete user privacy while providing more reliable presence detection than conventional PIR sensors in the cultivation space, addressing both the functional monitoring requirements and the critical social-psychological factors affecting technology acceptance [15].

Our framework, implemented for the ESP32-C3 microcontroller architecture, establishes personalized activity baselines through pattern recognition algorithms while optimizing power management, wireless connectivity, and non-intrusive interaction within indoor gardening environments. The system utilizes the owl's mechanical capabilities, which are nodding motions, vibration, and audio feedback, to provide both plant care reminders (watering schedules, fertilization timing, seasonal planting cues) and wellness check prompts in a socially acceptable manner [16] that enhances the overall gardening experience. The entire implementation is available as an open-source project on GitHub https://github.com/anh0001/esp32-owl-companion.git, enabling reproducibility and further development by the research community and home gardening enthusiasts.

Garden Watch operates through a workflow that balances monitoring with user dignity. The system begins with a learning phase to establish personalized activity baselines in the garden space. During operation, sensors detect human presence at regular intervals, with local data processing ensuring privacy. The owl delivers dual-purpose interactions through nodding, audio tones, and vibration that serve both as gardening reminders and wellness checks. When activity patterns deviate from baselines, the system can increase interactions or alert caregivers. This approach enables Garden Watch to function simultaneously as a gardening companion and monitoring system without the stigma of traditional health technologies.

## 2. Proposed Method

Garden Watch is an open-source framework designed for non-intrusive behavioral monitoring of the elderly. It utilizes a zoomorphic garden statue to integrate seamlessly into the therapeutic context of home gardening. This approach avoids the clinical aesthetics of traditional monitoring systems, harnessing gardening's proven benefits, including physical activity, cognitive enhancement, and emotional well-being.

Our research integrates passive monitoring with a zoomorphic design in the therapeutic gardening context, extending beyond indoor-focused prior work to outdoor spaces, enhancing elderly well-being, and overcoming social-psychological adoption barriers.

The framework consists of three integrated components: (1) a physical zoomorphic design in the form of a steel owl statue, (2) a hardware implementation based on the ESP32-C3 microcontroller architecture, and (3) a software system for behavioral pattern recognition and interaction management.

### 3.1 Zoomorphic Design Implementation

The system is embodied in a 200mm steel owl statue with a detachable 100mm head and 75mm bowl-shaped body, as shown in Fig. 2. It leveraging zoomorphic, non-clinical traits to minimize medical stigmatization [13], [14].

The owl integrates seamlessly into garden settings without hinting at medical monitoring. It features a nodding mechanism (15° forward, 10° back), audio, and vibration for plant care and health prompts. The body encases electronics while retaining garden-appropriate aesthetics, with a magnetic detachable head for maintenance and a bronze or copper finish enhancing its decorative, unobtrusive monitoring role.

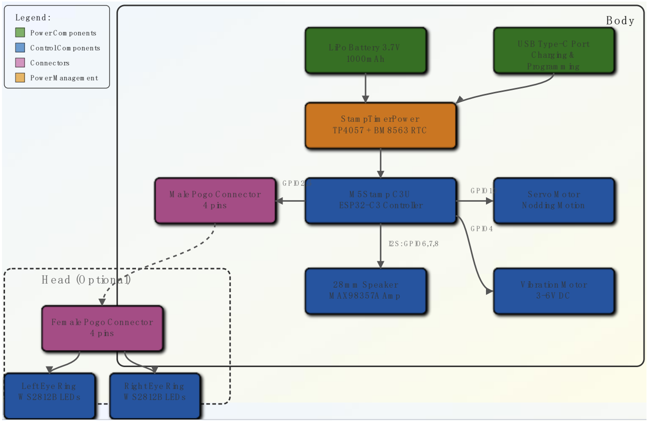


Fig. 3. System architecture diagram of Garden Watch, depicting power (battery, management), control (ESP32-C3), and interface connections, with a modular detachable head balancing functionality and aesthetics.

### 3.2 Hardware Architecture

The system leverages the M5Stamp C3U with an ESP32-C3 RISC-V processor (160MHz), chosen for its power efficiency, Wi-Fi connectivity (802.11 b/g/n), and adequate processing power for pattern recognition, supporting extended battery-powered operation.

The StampTimerPower module manages battery charging, 3.3V/5V regulation, and real-time clock functions, powered by a 3.7V 1000mAh LiPo battery with USB-C charging. User feedback is enabled via a 28mm speaker with an amplifier and a vibration motor for audio-haptic interaction.

Fig. 4. Bottom layer of Garden Watch contains the audio subsystem (28mm speaker, MAX98357A amplifier) in a 3D-printed housing, supporting non-intrusive feedback for plant care and wellness checks.

Fig. 5. Middle layer implementation showing the power and motion subsystems, including the LiPo battery (1000mAh), servo motor for nodding motion, and mini vibration motor for haptic feedback. This arrangement optimizes weight distribution while maintaining the garden ornament's aesthetic exterior.

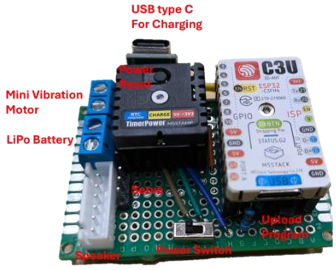


Fig. 6. Top layer with control circuitry (M5Stamp C3U, ESP32-C3; StampTimerPower), optimized for functionality and compactness, with capacitors addressing audio interference.

We stacked the hardware bottom (Fig. 4), middle (Fig. 5), and top (Fig. 6) layers to create a modular design as shown in Fig. 7.

In practice, we found a noise from the boost converter was mitigated by integrating filter capacitors at the battery input and BAT_OUT pins, ensuring stable power and minimal audio interference. Software restrictions on vibration motor duration prevent voltage drops from impacting the 5V boost converter.

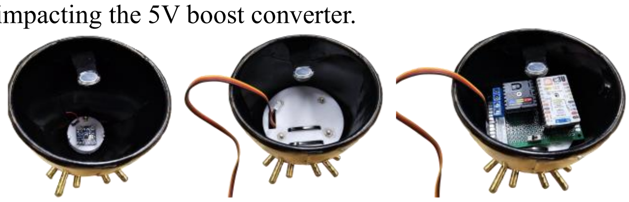

Fig. 7. Modular assembly of Garden Watch, stacking functional layers for easy installation and maintenance, ensuring serviceability and aesthetic, non-clinical design.

A dedicated module, shown in Fig. 8, employs AMG8833 (8×8 IR) and VL53L5X (8×8 ToF) sensors connected to the ESP32-C3 architecture for privacy-preserving human detection.


Fig. 8. Privacy-preserving sensor module hardware, compactly integrating AMG8833 (8×8 thermal) and VL53L5X (8×8 ToF) sensors, 1.8cm apart, with ESP32-C3, enabling separate wireless monitoring.

Unlike PIR sensors, this module identifies stationary human presence via temperature (22-31°C) and depth data, reducing false positives and aligning with elderly monitoring acceptance [17].

### 3.3 Software Framework

The software framework, as shown in Fig. 3, implements three core functions: activity monitoring, pattern recognition, and user interaction.

#### 3.3.1 Activity Monitoring Algorithm

This algorithm combines thermal and depth sensor data to accurately detect human presence.

**Thermal sensor data processing:** The thermal sensor captures temperature readings in an $8 \times 8$ grid. Human body temperature typically ranges from 22°C to 31°C at the sensor's detection range. $T(i,j)$ is thermal reading at position $(i,j)$ in the $8 \times 8$ grid.

$$H(i,j) = \begin{cases} 1, & \text{if } 22°\text{C} \leq T(i,j) \leq 31°\text{C} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

**Depth sensor validation:** The depth sensor ensures detected heat sources are within a specific range, minimizing false positives. $D(i,j)$ is depth reading at position $(i,j)$ at time $t$, $D_{prev}(i,j)$ is the previous reading at time $t-1$, and $\Delta D(i,j) = |D(i,j) - D_{prev}(i,j)|$.

$$V(i,j) = \begin{cases} 1, & \text{if } D_{min} \leq D(i,j) \leq D_{max} \text{ } AND \text{ } \Delta D(i,j) \geq D_{th} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where $D_{min}$ and $D_{max}$ define the attention range for human detection (typically 0.5m to 3m) and $D_{th}$ is the minimum change required to indicate movement (typically 5-10cm depending on sensor sensitivity).

**Human presence detection:** Combining thermal and depth sensor validation results to confirm human presence.

$$C(i,j) = H(i,j) \cdot V(i,j) \quad (3)$$

$$\text{P} = \begin{cases} 1, & \text{if } \sum_{i=0}^{7} \sum_{j=0}^{7} C(i,j) \geq \theta_P \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

Where $\theta_P$ is a threshold indicating the minimum number of valid pixels required to confirm presence (typically 3-5 pixels).

This method enhances detection reliability over traditional PIR sensors, upholding low power needs and user privacy, consistent with privacy-focused techniques critical for acceptance [18].

#### 3.3.2 Pattern Recognition Algorithm

This algorithm identifies deviations from established daily and weekly activity patterns, helping to detect unusual behaviors early.

**Daily activity presence:** The system logs activity within hourly slots each day $A_d(t)$ is activity presence during an hour on the day $d$.

**Baseline weekly pattern:** An average pattern of user activity is calculated over multiple weeks to create a reliable reference:

$$B(t,w) = \frac{1}{N} \sum_{d=1}^{N} A_{d+7(w-1)}(t) \quad (5)$$

Where $w \in \{1,2,\ldots,7\}$ represents the days of the week.

**Deviation detection:** The standard deviation is calculated to quantify typical variability in user activity:

$$\sigma(t,w) = \sqrt{\frac{1}{N} \sum_{d=1}^{N} \left(A_{d+7(w-1)}(t) - B(t,w)\right)^2} \quad (6)$$

**Activity deviation score:** This measures how significantly current activity deviates from the expected pattern:

$$S_d(t) = \frac{|A_d(t) - B(t,w_d)|}{\sigma(t,w_d) + \epsilon} \quad (7)$$

Where $w_d$ is the current day of the week, and $\epsilon$ prevents division by zero.

**Alert generation:** Alerts are generated if the deviation exceeds a predefined threshold:

$$Alert_d = \begin{cases} 1, & \text{if } \sum_{t=1}^{24} S_d(t) \geq \theta_A \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

Where $\theta_A$ sets the sensitivity of the alert system.

This approach is supported by research demonstrating that personalized baselines enable the detection of health changes up to 11 days before adverse events [6].

Upon detecting deviations, the system triggers local notifications via the owl's features or remote Wi-Fi alerts, ensuring timely information for users and caregivers

#### 3.3.3 User Interaction Algorithm

This algorithm schedules interactions to remind users of plant care tasks and perform wellness checks based on activity.

**Plant care reminder scheduling:** Reminders are periodically scheduled based on the frequency and preferred time:

$$R_{plant}(d,t) = \begin{cases} 1, & \text{if } \left(d \text{ } mod \text{ } f_{plant}\right) = 0 \text{ and } t = t_{plant} \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

**Wellness check prompts (based on inactivity):** The system prompts interactions during periods of inactivity in usual activity time windows:

$$I_d(t) = \begin{cases} 1, & \text{if} \sum_{i=t-\Delta t}^{t} A_d(i) = 0 \text{ and usual activity time} \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

Where $\Delta t$ defines the inactivity threshold.

**Interaction decision:** The interaction type is determined based on the scheduled reminders or detected inactivity/alerts:

$$M(t) = \begin{cases} M_{plant}, & \text{if } R_{plant}(d,t) = 1 \\ M_{wellness}, & \text{if } I_d(t) = 1 \text{ or } Alert_d = 1 \\ M_{normal}, & \text{otherwise} \end{cases} \quad (11)$$

Interaction modes $M_{plant}$, $M_{wellness}$, and $M_{normal}$ utilize combinations of audio feedback, nodding movements, and vibration cues.

The interaction design deliberately avoids complex voice commands or screen-based interfaces that prior research has identified as barriers for elderly users [16]. Instead, basic physical interactions (such as a person's appearance) provide sufficient feedback while remaining accessible to users with varying levels of technical literacy.

## 3. Experiments

Garden Watch employs a RESTful HTTP API for remote control and monitoring of the owl robot. The API integrates with healthcare systems and is testable via standard tools. Key endpoints include /status (GET) for device state (battery, detection), /control/motion (POST) for nodding motion, /control/audio (POST) for audio feedback, /control/vibration (POST) for haptic feedback, and /data/activity (GET) for historical data.

The Garden Watch sensor module adopts an energy-efficient approach, sampling at 5-minute intervals using AMG8833 thermal and VL53L5X depth sensors to detect a human presence (22-31°C range) with local processing. Hourly statistical summaries (detection counts, averages) are transmitted via the RESTful API, reducing communication overhead and enhancing battery life, while low-resolution 8×8 grids, as shown in Fig. 9.

Fig. 9. Sensor output comparison: (A) AMG8833 (8×8 thermal) showing human signature, (B) VL53L5X (8×8 ToF) with distance data, (C) RGB reference (development only). Low-resolution sensors (A, B) enable reliable, privacy-preserving presence detection.

The Garden Watch framework was evaluated through experiments monitoring garden activity patterns using simulated data from typical elderly gardening behaviors, testing pattern recognition and alert generation. Daily garden engagement analysis established healthy baseline rhythms, with peaks at 80-90% (6-8am), 60-70% (10am-12pm), and 70-80% (5-7pm), and <10% nighttime activity (10pm-5am), which is shown in Fig. 10.

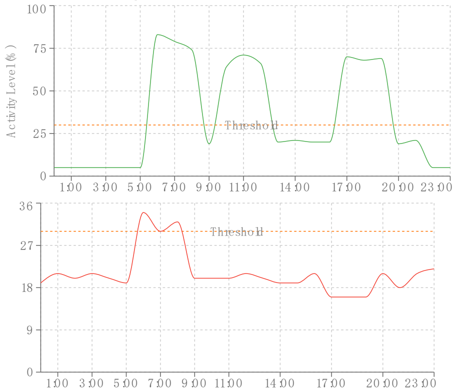


Fig. 10. Comparison of healthy versus concerning daily garden activity patterns. Healthy behavior (top) shows expected peaks during morning garden checks (6-8am), midday maintenance (10am-12pm), and evening care (5-7pm), while concerning patterns (bottom) exhibit reduced daytime gardening engagement and elevated nighttime activity.

The concerning pattern exhibited reduced activity: 30-35% morning, 20% midday, 15-20% evening, and elevated 20% nighttime activity.

Weekly analysis showed healthy patterns with 3-5 tasks and 40-70 minutes daily, versus concerning patterns with 0-1 tasks, <20 minutes, and irregular engagement.

Longitudinal four-week monitoring showed stable deviation scores (<0.5) in weeks 1-2, rising above 1.5 in weeks 3-4 Fig. 11, detecting changes 8-10 days early, align with prior findings of 11-day detection windows.

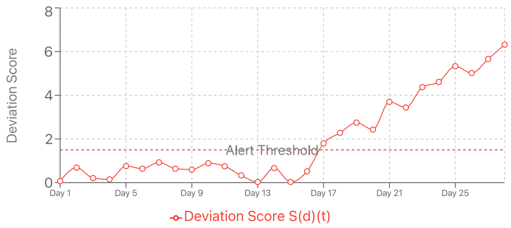


Fig. 11. Displays the deviation score analysis calculated using Eq. 7 from our framework.

Our experimental results yielded several important insights. The Garden Watch framework successfully identified behavioral changes before they reached critical thresholds, providing a valuable early warning system. By embedding monitoring within natural gardening activities, the system gathered meaningful health insights without the stigmatizing appearance of conventional medical technology. The combination of daily rhythm analysis, weekly task completion tracking, and response time monitoring provided a comprehensive view of well-being. The deviation score Eq. 7 effectively distinguished normal variations from the concerning changes. Additionally, the zoomorphic owl design avoided clinical appearance, addressing a primary barrier to technology adoption among elderly populations. Future work targeting real-world validation and algorithm refinement.

## 4. Conclusions

This research introduces Garden Watch, an open-source framework that integrates behavioral monitoring within a zoomorphic garden statue. By leveraging the therapeutic benefits of home gardening, a widely practiced activity that promotes physical, cognitive, and emotional well-being among older adults. Our approach offers a potential solution to the stigmatization and clinical appearance that typically hinder technology adoption. The ESP32-based implementation demonstrates how monitoring can be embedded within familiar, aesthetically pleasing objects that preserve dignity and autonomy. While further evaluation is needed to assess long-term adoption, this work contributes an accessible, reproducible foundation for developing non-intrusive monitoring solutions that respect both the technical and psychosocial needs of elderly users.

## Acknowledgment

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