Objective Assessment of Daily Behavior in a Smart Home using Longitudinal Sensor-Based Metrics

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***Abstract*—Human behavior in residential environments follows structured temporal and spatial patterns reflecting daily routines and mobility. Continuous and unobtrusive monitoring of such behavior is relevant for preventive and longitudinal assessment but remains challenging due to noise, variability, and sparsity of ambient sensor data. We present a smart home–based framework for long-term behavioral monitoring using distributed ambient sensors. The system integrates six ultrasonic distance sensors, three pressure sensors, two load cells, and one contact reed sensor deployed across five functional zones of a smart living laboratory. Data were collected during an eight-week weekday study under regular living conditions and processed using a zone-aware pipeline with event validation, filtering, and aggregation. We derived behavioral metrics including zone-level activity, zone-to-zone transitions, walking speed, short-dwell fraction, and a routine stability index (RSI). Participants exhibited stable yet week-dependent indoor mobility patterns. Mean daily walking speed ranged from 0.37 to 0.73 m/s, short-dwell events (<60 s) accounted for 28–55% of room visits, and zone-to-zone transitions ranged from 40 to 150 per day. RSI values indicated consistent weekday routines with moderate week-to-week variability. These results demonstrate that sparse binary ambient sensor data can be transformed into reproducible behavioral metrics for longitudinal smart home monitoring.**

***Index Terms*—smart home monitoring, ambient sensors, behavioral metrics, longitudinal analysis, routine stability.**

I. Introduction

Human behavior in residential environments exhibits structured temporal and spatial patterns that reflect daily routines, mobility, and interaction with the surrounding space [1]. These patterns are shaped by physiological capacity, cognitive state, and psychological well-being, and they evolve gradually over time rather than changing abruptly [2]. Consequently, longitudinal observation of everyday behavior provides access to information that is typically not captured by episodic clinical assessments or short-term experimental studies [3].

In many application domains, including preventive healthcare, mental health-monitoring, and cognitive aging research, behavioral change is of interest precisely because it often precedes overt functional impairment [4]. Changes in activity intensity, fragmentation of daily routines, altered movement dynamics, or reduced regularity of spatial usage have been reported as early correlates of declining health status [5]. However, capturing such changes requires continuous observation under real-world conditions, as well as quantitative metrics that remain stable in the presence of noise and variability inherent to everyday life [6].

Existing approaches to behavioral assessment face practical and methodological limitations. Wearable devices can provide high-resolution physiological and motion data, but their long-term use is constrained by user compliance, charging requirements, and device abandonment [7]. Questionnaire-based assessments are subjective and temporally sparse, while clinical evaluations are typically performed in artificial environments and at coarse time scales [8]. Vision-based monitoring systems raise privacy concerns and are often unsuitable for long-term deployment in private living spaces [9]. These constraints motivate infrastructure-based sensing approaches that operate passively and continuously without requiring user interaction [4].

Smart home environments equipped with distributed sensors offer a viable alternative for long-term behavioral monitoring. By embedding sensors in the living space rather than on the individual, smart homes enable unobtrusive acquisition of activity-related data during normal daily routines [3], [10]. Prior work has demonstrated the feasibility of extracting activity patterns and routines from such environments; however, translating raw event streams into reproducible behavioral descriptors remains challenging [11]–[15]. Binary sensors such as ultrasonic distance sensors, pressure sensors, and contact switches generate robust but sparse data, requiring careful filtering, spatial validation, and temporal aggregation before meaningful behavioral interpretation is possible.

A main challenge in smart home–based monitoring is therefore the transformation of heterogeneous, event-driven sensor data into reproducible behavioral descriptors. Metrics must be robust to missing data, adaptable to individual living patterns, and interpretable across long observation windows. Single indicators are often insufficient; activity intensity, locomotion characteristics, temporal fragmentation, and routine regularity capture complementary aspects of behavior and should be considered jointly. Furthermore, longitudinal analysis requires consistent aggregation strategies that allow week-to-week comparison while preserving intra-week variability.

In this work, we present a smart home monitoring framework that addresses these challenges through a multi-sensor infrastructure, a validated data acquisition and filtering pipeline, and a set of complementary behavioral metrics derived from long-term residential data. We deploy ultrasonic distance sensors, pressure sensors, and contact sensors across multiple functional zones and collect continuous event streams during weekday operation. From these data, we compute zone transitions, walking speed, short-dwell fraction, and a routine stability index (RSI), alongside posture-related measures and zone-based residence times. In addition, the system supports real-time visualization through trajectory tracking and zone-based heat maps, enabling continuous observation of spatial behavior.

Our work contributes:

1) the design and deployment of a zone-aware smart home sensing infrastructure for continuous behavioral monitoring;
2) a processing pipeline that converts raw sensor events into validated behavioral metrics suitable for longitudinal analysis; and
3) an empirical evaluation of activity dynamics, mobility, fragmentation, and routine stability over multiple weeks under real-world conditions.

II. Materials and Methods

Here, we describe the smart home system, sensor deployment, study design, and behavioral metric definitions.

A. Smart Home Environment and System Architecture

We conducted the study in a 35 m^2 smart living laboratory. The apartment comprised five functional zones: entrance corridor, kitchen (sink, refrigerator, oven), living room (sofa, sofa bed, television), bedroom (single bed), and bathroom (toilet, sink, shower) (Fig.1). This environment represents a realistic home setting in which daily activities are performed naturally, without imposed routines. The technical infrastructure of the apartment builds on a wire-based, bus-based intelligent system (BASIS) to support sensor deployment, communication, and data acquisition [3]. We connected our sensors to BASIS either directly via wired interfaces or indirectly via wireless transmission using Bluetooth. Battery-powered sensors that could not be wired due to obtrusiveness or deployment constraints transmitted data using ESP32 microcontrollers (Espressif Systems, Shanghai, China) to a central gateway, a Raspberry Pi 4B (Raspberry Pi Foundation, Cambridge, UK). Sensor events were encoded as binary triggers containing a sensor identifier and timestamp. The central embedded gateway collected sensor events via a bus coupler for data storage, real-time visualization, and offline analysis.

B. Sensor Deployment and Zone Definition

We deployed a heterogeneous set of ambient sensors to capture presence and movement across the smart home environment. In total, the system comprised six ultrasonic distance sensors, three pressure sensors, one contact reed sensor, one weight scale, and one load cell.

We mounted the ultrasonic distance sensors (HC-SR04, Elecfreaks, Shenzhen, China) on doorframes or walls at zone boundaries. These sensors were operated in 3 Hz in a binary triggering mode and configured to activate when an inhabitant crossed the sensor's field of view. They were not used for distance estimation but exclusively for zone discrimination and detection of transitions between areas.

We integrated pressure sensors (FSR-402, Interlink Electronics, Camarillo, CA, USA) into chairs and sofas to detect sitting activity. These sensors were battery-powered, transmitted data via BLuetooth, and provided binary occupancy information.

We installed a wired contact reed sensor (magnetic reed switch; Satel Ltd., Gdańsk, Poland) on the toilet lid to detect bathroom-related interaction events. Additionally, a digital weight scale equipped with a strain-gauge load cell (CK-series single-point load cell; KERN & SOHN GmbH, Balingen, Germany) was installed in the bathroom to capture additional interaction signals.

The entrance corridor, hallway, and central corridor areas were treated as a noisy (linking) zone, representing transitional movement rather than purposeful activity (Fig. 1). We used the sensor activations within this zone to validate movement continuity between functional zones, but they were not interpreted as standalone behavioral activities.

C. Participants and Study Design

We conducted this study as a long-term system validation experiment to evaluate the functionality and robustness of the smart home monitoring infrastructure under real-world usage conditions. Data collection took place over approximately eight consecutive weeks.

Three male graduate students (23±2 years) used the monitored environment during the study period as part of their regular laboratory work. Participants accessed the smart home environment according to their individual schedules and were not assigned predefined days or time slots. While present, they performed routine development, maintenance, and testing activities unrelated to the monitoring system.

We enforced single-occupancy conditions throughout data collection. In rare cases where simultaneous presence was unavoidable, participants documented the affected time intervals manually, and we excluded these segments from subsequent analysis. Participants recorded entry and exit times using written notes at the moment of access, which we later used to cross-check the automatically collected sensor data. We did not instruct participants to perform any specific tasks or behaviors for the purpose of this study. We applied no behavioral interventions, and the system collected all data passively through the installed ambient sensors. A visible notice informed all occupants that data collection was in progress throughout the study period.

The study focused exclusively on validating system performance and data quality under realistic conditions and did not aim to assess participant behavior or clinical outcomes.

D. Activity Inference and Behavioral Metrics

We describe the inference of coarse activity states from ambient sensor events and the derivation of quantitative behavioral metrics used for longitudinal analysis. All metrics were

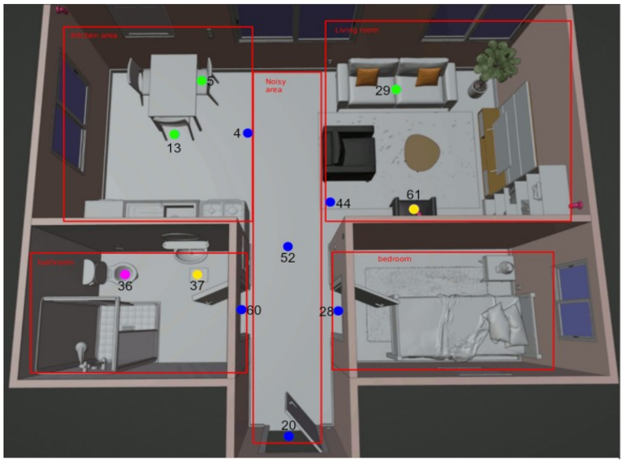

Fig. 1: Smart home floor plan with sensor deployment. Blue markers indicate ultrasonic distance sensors for zone transition detection, green markers pressure sensors for sitting detection, the yellow marker a load-cell–based weight scale, and the pink marker a contact reed sensor on the toilet lid.

computed from validated sensor triggers and aggregated at the day and week level to capture activity intensity, locomotion characteristics, temporal fragmentation, and routine stability. We use the term locomotion to denote aggregated movement-related behavior derived from walking episodes, zone transitions, and short-dwell activity, rather than a distinct posture

We computed behavioral metrics from the cleaned weekday event stream $\mathcal{E} = \{(t_i, s_i)\}_{i=1}^{N}$, where t_i is the timestamp and s_i the sensor ID. Events were filtered by (i) discarding repeated triggers of the same sensor within $\Delta t_{\text{min}} = 300$ ms, and (ii) retaining only adjacent transitions $\mathcal{A}(s_{i-1}, s_i) = 1$, where $\mathcal{A}(\cdot, \cdot)$ encodes the predefined sensor adjacency graph. All analyses were restricted to weekdays within 08:00–18:00 and to valid monitoring segments without gaps $> \tau$ with $\tau = 15$ min.

- Valid monitoring time: Let $\Delta_i = t_i - t_{i-1}$ for $i = 2, \dots, N$ denote inter-event gaps (after filtering). We segment each day into maximal contiguous sequences in which all consecutive gaps satisfy $\Delta_i \le \tau$. Let $[t_{k,\text{start}}^{(d)}, t_{k,\text{end}}^{(d)}]$ denote the k-th valid segment in day d. The valid monitoring time for day d is

$$T_{\text{valid}}^{(d)} = \sum_{k=1}^{K_d} \left(t_{k,\text{end}}^{(d)} - t_{k,\text{start}}^{(d)} \right) \tag{1}$$

and weekly valid time is $T_{\text{valid}}^{(w)} = \sum_{d \in w} T_{\text{valid}}^{(d)}$.

- Zone transitions per day: Let $z(s)$ map each sensor ID to a zone label. A zone transition occurs when $z(s_{i-1}) \neq z(s_i)$ for two consecutive valid events. The number of transitions in day d is

$$N_{\text{tr}}^{(d)} = \sum_{i \in \mathcal{I}_d} \mathbf{1}[z(s_{i-1}) \neq z(s_i)] \tag{2}$$

where $\mathcal{I}_d \subseteq \{2, \dots, N\}$ indexes valid events in day d and $\mathbf{1}[\cdot]$ is the indicator function. Weekly transitions per day are reported as mean $\pm$ standard deviation (SD) across weekdays.

- Short-dwell fraction: We define dwell time at event i as $\delta_i = t_{i+1} - t_i$ for $i = 1, \dots, N-1$. Short dwell events satisfy $\delta_i < \delta_0$ with $\delta_0 = 60$ s. For day d, the short-dwell fraction is

$$f_{\text{SD}}^{(d)} = \frac{\sum_{i \in \mathcal{J}_d} \mathbf{1}[\delta_i < \delta_0]}{|\mathcal{J}_d|} \tag{3}$$

where $\mathcal{J}_d$ indexes valid dwell events in day d (excluding the final event of the day).

- Walking episodes and speed: Walking episodes are sequences of at least two consecutive valid ultrasonic triggers with adjacent sensor IDs. For each adjacent step $(s_i \to s_{i+1})$, a predefined distance $D(s_i, s_{i+1})$ is used, and the step speed is

$$v_i = \frac{D(s_i, s_{i+1})}{t_{i+1} - t_i} \tag{4}$$

Weekly walking speed is reported as mean $\pm$ SD of $\{v_i\}$ over all valid walking steps.

- Routine stability index (RSI): For each day d, we form a nonnegative activity vector $\mathbf{x}^{(d)} \in \mathbb{R}_{\geq 0}^{M}$ by aggregating dwell times in fixed zone–time bins (e.g., zone $\times$ hour-of-day). $\text{RSI}^{(w)}$ for week w is computed as the average cosine similarity between all weekday pairs:

$$\text{RSI}^{(w)} = \frac{2}{|\mathcal{D}_w|(|\mathcal{D}_w| - 1)} \sum_{\substack{d_1 < d_2 \\ d_1, d_2 \in \mathcal{D}_w}} \frac{\mathbf{x}^{(d_1)} \cdot \mathbf{x}^{(d_2)}}{\|\mathbf{x}^{(d_1)}\|_2 \, \|\mathbf{x}^{(d_2)}\|_2} \tag{5}$$

To quantify within-week variability, we reported the SD of the set of pairwise cosine similarities used in Eq. (5).

E. Visualization and Reporting

The system supports real-time and offline reporting. A real-time route-tracking maps visualized movement trajectories across the floorplan. A zone-based heat map displays cumulative residence time using a green-to-red color scale (2 hours increments). Offline reports provide tabular summaries and graphical representations, including weekly trends of activity, locomotion, and routine metrics.

To avoid influencing participant behavior, we derive all results from the offline pipeline without real-time feedback.

III. Results

The smart home system operated in a continuous active monitoring mode during valid periods. We computed and reported metrics from weekdays only.

Walking speed ranged between weekly mean values of 0.37 and 0.73 m/s, with corresponding SD between 0.12 and 0.62 m/s across study weeks (Fig. 2).

The mean number of zone-to-zone cumulative transitions per day decreased substantially after the first study week.

Across study weeks 2–8, mean daily transitions ranged from approximately 40 to 150 transitions/day, with week-specific variability reflected by SD values between ±30 and ±180 transitions/day (Fig. 2).

The short-dwell fraction varied across study weeks. Weekly mean short-dwell fractions ranged from 0.37 to 0.83, with SD values between ±0.15 and ±0.36. This metric was computed across all zones and reflects the temporal structure of activity without spatial weighting.

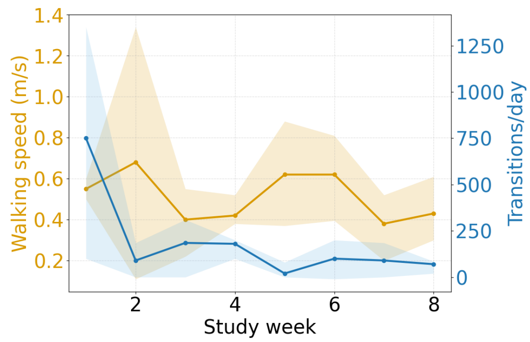

Fig. 2: Weekly mean ± SD of daily zone-to-zone transitions and walking speed, computed from weekday data only.

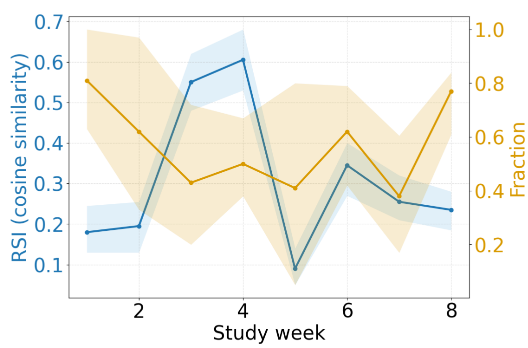

Fig. 3: Short-dwell fraction and RSI across study weeks.

RSI exhibited week-to-week variability. Weekly mean RSI values ranged from 0.09 to 0.61, with corresponding SD values between ±0.04 and ±0.08 (Fig. 3).

Across the study period, the total aggregated mean daily trigger count across all zones ranged from approximately 90 to 750 triggers/day, with the highest values observed in the early study weeks (Fig. 4-top). The noisy zone consistently contributed the largest share of triggers, with mean daily counts ranging from approximately 20 to 220 triggers/day. The living room and kitchen zones exhibited moderate activity, typically contributing 20–60 triggers/day and 10–35 triggers/day, respectively. The bathroom and bedroom zones showed lower activity levels, generally remaining below 20 triggers/day, except for isolated weeks with elevated bedroom activation. All values represent raw binary sensor activations after data cleaning, and the total bar height reflects the sum of triggers across all zones. Hourly trigger intensity exhibited a pronounced midday concentration, with peak activity occurring between

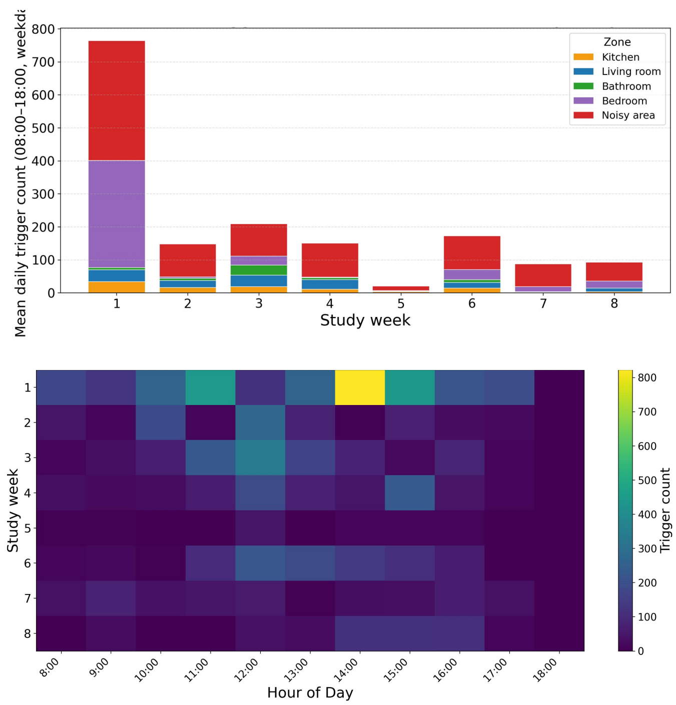

Fig. 4: Zone-level and temporal distribution of sensor-trigger activity. Mean daily sensor-trigger counts aggregated by zone for each study week (top) and hourly distribution of sensor-trigger intensity across weekdays (bottom). The counts reflect binary sensor activations and therefore represent zone-local interaction intensity rather than unique movements. Color intensity indicates the number of triggers within each hour bin. Triggers may contribute to multiple zones during transitions.

12:00 and 15:00 (Fig. 4-bottom). The highest hourly trigger counts reached approximately 750–800 triggers/hour, while early morning (08:00–09:00) and late afternoon (after 17:00) periods consistently showed low activity (<50 triggers/hour).

IV. Discussion

This work demonstrated the feasibility of long-term, unobtrusive behavioral monitoring in a smart home environment using a heterogeneous sensor infrastructure. Across multiple weeks of weekday monitoring, the system enabled the extraction of complementary behavioral metrics, including zone transitions, walking speed, activity fragmentation, and RSI. In addition, real-time visualization through trajectory tracking and zone-based heat maps was continuously available alongside offline statistical analysis (Fig. 5).

Daily behavior in residential environments is characterized by strong regularities, and deviations from established routines may precede overt functional impairments. Metrics such as transition frequency, short-dwell fraction, and routine stability capture different aspects of behavioral organization, including activity intensity, temporal fragmentation, and consistency across days. The longitudinal nature of the collected data allows the establishment of individualized baselines, enabling future detection of gradual or abrupt changes relative to a person's own habitual patterns rather than population-level thresholds.

From a preventive healthcare perspective, continuous in-home monitoring offers the opportunity to observe behavioral dynamics over extended periods without requiring active user participation. The presented framework illustrates how low-level sensor events can be transformed into higher-level behavioral descriptors that may support risk stratification, longitudinal assessment, and early intervention strategies. Such approaches are particularly relevant in preventive settings, where subtle behavioral changes may be more informative than isolated measurements.

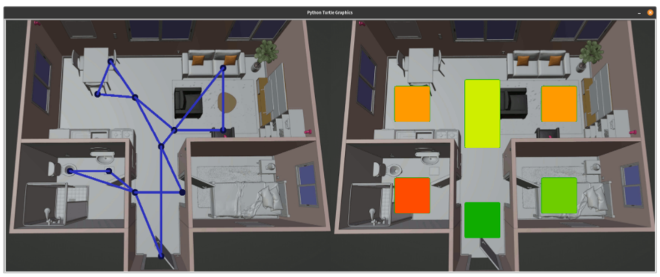

Fig. 5: Real-time visualization of in-home activity. Left: trajectory-based movement tracking reconstructed from consecutive ultrasonic sensor triggers. Right: zone-based residence-time heat map, where color intensity (green → yellow → orange → red) indicates increasing accumulated presence during the monitoring period.

Although the present study does not include clinical populations, the extracted behavioral metrics are conceptually aligned with indicators discussed in the literature on mental health and cognitive aging [16]. Alterations in daily structure, activity fragmentation, and routine regularity have been associated with conditions such as depression, mild cognitive impairment, and dementia [17]. The proposed smart home monitoring approach may therefore provide a foundation for future studies investigating behavioral markers in these domains, while emphasizing that clinical validation is required before diagnostic or prognostic use.

Compared to wearable or questionnaire-based approaches, the smart home setup enables passive, continuous monitoring in a naturalistic environment, minimizing compliance burden and reactivity effects. The combination of real-time visualization (route tracking and heat maps) with offline analytics enhances interpretability and supports both exploratory analysis and long-term observation. Importantly, sensing is embedded in the environment rather than attached to the individual, allowing monitoring to occur without disrupting daily routines.

This study is limited by its deployment in a single residential environment and the absence of ground-truth annotations for posture or activity. Behavioral states were inferred from sensor configurations rather than directly measured. In addition, no clinical assessments were conducted, and findings should be interpreted as methodological validation rather than evidence of clinical utility.

Future work will focus on multi-resident deployments, larger cohorts, and longer observation periods, as well as the integration of physiological or wearable data streams. Learning-based models for individualized change detection and anomaly identification represent a further step toward predictive behavioral health monitoring in real-world settings.

V. Conclusion

This work presented a smart home framework for longitudinal behavioral monitoring using distributed ambient sensors and zone-aware analysis. The system integrated 12 sensors: six ultrasonic distance sensors, three pressure sensors, two load cells, and one contact reed sensor via a building automation bus. A filtering and validation pipeline was implemented to handle repeated triggers, missing events, and invalid transitions. Using eight study weeks of weekday data, we demonstrated that sparse, binary sensor triggers can be aggregated, and mapped to reproducible behavioral descriptors, including zone-transition activity, walking speed, dwell-time characteristics, and RSI. The total mean daily sensor-trigger count ranged from approximately 90 to 750 triggers/day, with the corridor zone contributing 40–220 triggers/day. Mean daily zone-to-zone transitions ranged from 40 to 150 transitions/day, while estimated walking speed remained within 0.37–0.73 m/s. Short-dwell events ($<$60 s) accounted for 28–55% of zone visits, and the RSI indicated consistent weekday activity patterns with measurable week-to-week variability.

The system also supports real-time trajectory tracking and zone-based heat-map visualization for continuous observation of spatial behavior. The results confirm that robust and interpretable longitudinal behavioral metrics can be derived from ambient smart home sensor data under real-world conditions, providing a scalable foundation for future studies on behavioral change and long-term residential monitoring.

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