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Data Descriptor

A Real-World Smart Home Dataset Integrating Sleep, Environmental, Physiological, and Ambient Sensing for Homecare Research

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Abstract

Modern homecare research increasingly relies on multimodal sensing technologies in smart homes to monitor daily routines, sleep, environmental conditions, and physiological activities over long periods. However, publicly available datasets often lack real-world longitudinal tracking, multimodal integration, and detailed environmental and wearable sensor data collected in real home environments. This paper introduces a multimodal smart home dataset, collected from 10 participants over approximately one month in a real-world residential environment. The dataset integrates various Internet-of-Things (IoT) sensing modalities, including motion sensors, door contact sensors, environmental sensors, wearable physiological monitoring devices, and under-mattress sleep tracking mats. The collected data includes timestamps of room occupancy, steps, sleep, heart rate, respiratory rate, snoring, temperature, humidity, and interactions within the home. All sensor data streams were represented using timestamps standardized to UTC and stored as structured event records, including user and sensor ids, measurement types, timestamps, and sensor values. The dataset was then organized into CSV (comma-separated values) files for each user to facilitate future research in areas such as smart home data analytics, behavior monitoring, sleep analysis, home assistance, homecare systems, activity recognition, anomaly detection, and digital twin-based homecare applications. This dataset aims to support the reproducibility of research in homecare and ambient assisted living (AAL) environments.

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Keywords: multimodal sensing; homecare monitoring; ambient assisted living; social care; digital health; sleep monitoring; internet-of-things

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1. Summary

The growing demand for homecare technologies and assisted living systems has accelerated the development of smart home environments capable of continuously monitoring daily activities, physiological conditions, and environmental information [1,2]. Multimodal smart home datasets play a central role in supporting research on behavior monitoring, sleep analysis, activity recognition, health-centric home healthcare systems, and intelligent

decision support applications [3–5]. However, many publicly available datasets are limited by short monitoring durations, controlled laboratory environments, limited detection methods, or inadequate integration of physiological and environmental information [6,7]. The comparison with publicly available datasets refers to research datasets released for reuse, including laboratory or scripted-activity datasets and smart-home datasets with more limited duration or modality coverage. Longitudinal datasets collected in real-world residential environments remain relatively scarce, especially those that integrate ambient sensing, wearable device data, sleep data, and environmental information into a unified framework [8,9].

This paper introduces a longitudinal multimodal dataset, constructed from data collected over approximately one month from 10 participants in their real-world living environments. Ten participants were selected purposively from older adults receiving homecare services who were willing to contribute residential sensor data. Preference was given to people aged 65 years or older who lived alone, consistent with the intended homecare context. One participant living with a spouse and two children was retained to provide a contrasting multi-person household scenario. The sample size reflected the feasibility-oriented nature of the deployment and the practical requirements of installing, supporting, and monitoring multiple sensing systems in private homes. As participants knew that sensing devices had been installed, their behavior may initially have been influenced by the deployment. Data collection began during the deployment period, and no separate adaptation phase was excluded. Consequently, a short-term observation or Hawthorne effect cannot be ruled out, particularly during the initial days of monitoring.

The sensor infrastructure integrates various IoT devices, including motion detectors, door sensors, environmental sensors, wearable devices, and under-mattress sleep tracking mats. Environmental sensing refers to measurements describing the physical indoor environment, including temperature and humidity. Ambient sensing refers to unobtrusive sensors embedded in the home environment that monitor occupant interactions and activities, such as motion sensors and door contact sensors. These sensors collectively provide continuous, timestamped measurements of room occupancy, routine patterns, indoor interactions, sleep states, heart rate, respiratory rate, snoring, temperature, humidity, and other environmentally relevant data.

This data was collected to support data analytics research in smart home, homecare monitoring, behavioral analysis, home assistance, and digital health applications. The published data retains the natural variability and operational characteristics of real-world residential sensor deployments, including heterogeneity in event frequencies and real-world user behavior. For ease of reuse and interoperability, the raw sensor observation data has been converted from JSON (JavaScript Object Notation) event streams to structured CSV files suitable for time series analysis, statistical modeling, and machine learning applications.

2. Data Description

The dataset is organized as timestamped records and stored in CSV format. Each observation corresponds to a sensor measurement collected by a specific sensing device at a specific time. All participants were anonymized using non-identifiable identifiers, and no personally identifiable information is retained in the published dataset. Recorded observations include a timestamp, anonymized participant identifier, sensor identifier, measurement type, and corresponding sensor value. Table 1 lists the main attributes included in the dataset structure.

Table 1. Primary dataset attributes.

Column	Data Type	Description	Example
timestamp	datetime	Coordinated Universal Time (UTC) timestamp representing the time of the sensor observation.	2025-11-06T12:34:55Z
user_id	string	Anonymized participant identifier.	user1
sensor_id	string	Unique identifier corresponding to the sensing device.	motion1
measurement	string	Measurement type produced by the sensor.	occupancy
value	float/string	Numerical or categorical sensor reading.	1

This detection infrastructure integrates a variety of heterogeneous sensors deployed throughout the residence. Motion detectors are installed in some rooms to track occupant activity and movement. Once these sensors detect movement within the monitored area, they generate event-based observation data, enabling analysis of movement patterns, room occupancy, and transitions between rooms. Additionally, door open/close sensors are installed on specific objects and entry points within the residence, such as the refrigerator, bathroom door, and front door to capture interactions related to the occupants' daily behaviors and habits.

Environmental sensors reported indoor temperature and humidity observations at device dependent intervals. This data provides contextual information about room conditions and changes in indoor comfort throughout the monitoring period. In addition to environmental sensing, wearable physiological monitoring was performed using smartwatch-based sensing devices capable of recording heart rate, step count, and calorie measurements. The dataset also includes measurements taken under the mattress, capturing sleep-related behaviors such as transitions between different sleep states, breathing information, heart rate, and snoring. Table 2 describes the sensing devices, published variables, measurement units, acquisition mechanisms, reporting behavior, triggering conditions, and value coding. Because internal hardware sampling rates were not recorded in the deposited files, the table distinguishes device-dependent reporting from the intervals observed in the normalized CSV export.

Figure 1 shows the total number of records collected by each participant in the dataset. The number of observations varied among users due to differences in daily routines, house layout, sensor-triggering frequency, and temporary interruptions in data collection during deployment. Observation counts varied with home layout, the number and placement of installed sensors, sensor-triggering behavior, participant routines, and temporary data interruptions. Consequently, differences in record counts should not be interpreted directly as differences in participant activity. Users 3 and 5 generated the most observations, while users 1, 7, 2, and 9 generated relatively fewer. Nevertheless, all participants provided substantial multimodal longitudinal data, covering approximately one month of follow-up.

Table 3 shows the characteristics and monitoring information of the participants. The 'Homecare Visits' column reports the participants' typical scheduled homecare visits, not visits by the research team. The metadata indicate that all homes received the same core modalities; motion-sensor counts varied from three to five according to residence layout, while each participant had three door contact sensors, two environmental sensors, one wearable, and one sleep sensor. During the monitoring period, user3 lived in multi-person households and user6 lived with a dog. Consequently, data collected by ambient sensors

such as motion detectors and door sensors, at times reflect the activities of other household members rather than solely those of the monitored participant. This is an inherent limitation of passive ambient sensing systems deployed in shared living environments. In contrast, wearable devices and sleep tracking data obtained from under-mattress sensors are specific to the individual participant, as these sensors are dedicated to their exclusive use. Therefore, such physiological and sleep-related data remain unaffected by the activities of other household members.

Table 2. Sensor devices, measured variables, acquisition mechanisms, reporting intervals, triggering conditions, and value coding.

Device/Model	Variable	Unit	Acquisition Mechanism	Sampling/Reporting Interval	Trigger	Possible Values/Coding
Aqara Motion Sensor	Occupancy	Binary	Passive infrared motion detection	Event-driven; no fixed reporting interval	Motion or device-status event	True/False
Aqara Motion Sensor	Illuminance	lux	Ambient-light reading	Device-dependent; observed median: approximately 32 s	Motion or device-status report	Non-negative numeric value
Aqara Door & Window Sensor	Contact/state	Binary	Magnetic reed-switch detection	Event-driven; no fixed reporting interval	Opening, closing, or status report	ON/OFF
Aqara Temperature & Humidity Sensor	Temperature	°C	Digital environmental sensing	Device/platform-dependent; observed median: approximately 13.5 min	Periodic and/or change-based report	Numeric value
Aqara Temperature & Humidity Sensor	Humidity	% RH	Digital environmental sensing	Device/platform-dependent; observed median: approximately 13.5 min	Periodic and/or change-based report	Numeric value
Withings ScanWatch	Heart rate	bpm	PPG-derived wearable summary	Device/cloud-dependent; observed median: approximately 8.4 min	Aggregated device or cloud export	Numeric value or missing
Withings ScanWatch	Steps	Count	Accelerometer-derived summary	Device/cloud-dependent; observed median: approximately 8.4 min	Aggregated device or cloud export	Non-negative integer or missing
Withings ScanWatch	Calories	kcal	Device-derived energy estimate	Device/cloud-dependent; observed median: approximately 8.4 min	Aggregated device or cloud export	Non-negative numeric value or missing
Withings Sleep Analyzer	Sleep state	Categorical	Under-mattress pneumatic sensing	Session-dependent; observed median: approximately 2 min	Sleep epoch or session	`0/1`; exact meanings require provider confirmation
Withings Sleep Analyzer	Heart rate	bpm	Ballistocardiography-derived measurement	Session-dependent; observed median: approximately 2 min	Sleep epoch or session	Timestamp–value mapping or missing
Withings Sleep Analyzer	Respiratory rate	breaths/min	Pneumatic-signal-derived measurement	Session-dependent; observed median: approximately 2 min	Sleep epoch or session	Timestamp–value mapping
Withings Sleep Analyzer	Snoring	Device-defined	Device-derived sleep inference	Session-dependent; observed median: approximately 2 min	Sleep epoch or session	Numeric or categorical device output

Notes: Observed intervals were calculated separately within each participant–sensor–measurement stream. They describe the temporal spacing of records in the normalized CSV export and should not be interpreted as internal hardware sampling frequencies. Exact hardware models, firmware configurations, nominal platform-reporting intervals, and sleep-state coding should be confirmed with the equipment provider. Pressure is documented in the sensor metadata but is absent from the published participant CSV files.

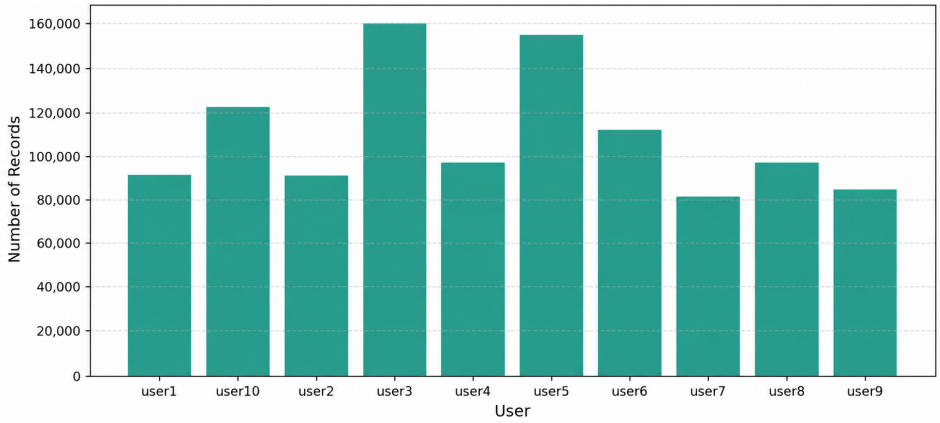

Figure 1. Total sensor records collected for each participant during the monitoring period.

Table 3. Participant characteristics and monitoring information.

User ID	Gender	Age Group	Living Arrangement	Homecare Visits	Days
user1	Male	85–89	Lives alone	2/day	34
user2	Male	85–89	Lives alone	2/day	33
user3	Male	59–64	Lives with wife and two children	4/day	33
user4	Female	75–79	Lives alone	2/day	33
user5	Female	90–94	Lives alone	3/day	33
user6	Female	90–94	Lives alone with a dog	3/day	28
user7	Female	85–89	Lives alone	3/day	29
user8	Female	79–84	Lives alone	2/day	29
user9	Female	79–84	Lives alone	1/week	28
user10	Female	95–99	Lives alone	2/day	27

Figure 2 illustrates the distribution of observational data across different detection methods. The WithingsIntraDay stream contributed the largest modality-specific count in the normalized release (181,725 records), followed by motion3 (141,865) and WithingsSleepRaw (141,380). Counts reflect measurement multiplicity, device-reporting behavior, sparsely populated measurement-specific fields, and event frequency and should not be interpreted as sampling-rate comparisons. In contrast, event-driven detection methods (such as door sensors) generated less observational data because data was only recorded during explicit interactions. Motion sensors generally generated a large amount of residential-related observational data, reflecting daily activities and room changes within the residential environment. Environmental detection methods (such as temperature and humidity sensors) generated a moderate density of observational data through periodic environmental measurements.

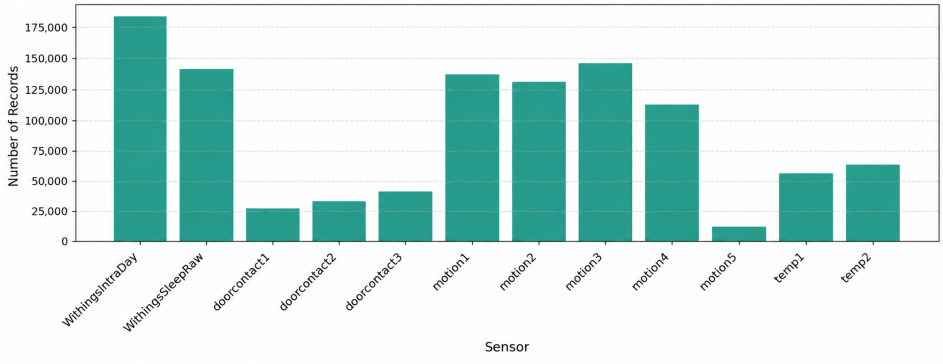

Figure 2. Total sensor records collected for each sensor during the monitoring period.

The published database contains raw sensor event files, sensor deployment information, and supplementary documentation to facilitate data reproducibility and reuse. The dataset also includes a metadata file describing each participant, sensor deployment, recording period, and sensor availability. This data is available in CSV format to ensure compatibility with common data analysis environments and machine learning frameworks, including Python 3.14, R 4.4.1, MATLAB R2024b, and other time series processing platforms.

3. Methods

3.1. Data Collection Environment

The data collection architecture is designed to ensure global consistency in deployment configuration across all residential environments, while accommodating differences in apartment size, room layout, and participant living conditions. All participants are equipped with the same core detection devices, including wearable physiological monitoring systems, under-mattress sleep tracking mat, environmental sensors, and door contact sensors. However, the number of motion sensors deployed varies depending on the physical characteristics of each residence. Smaller apartments are equipped with at least three motion sensors, while larger residences are equipped with up to five, ensuring adequate coverage of the living room, bedrooms, kitchen, and bathroom.

Figure 3 is an illustrative layout rather than a common floor plan. Residence size, room configuration, household composition, and installed motion-sensor count varied. These contextual differences limit direct comparison of raw event counts across participants. Motion sensors were deployed in each room such as bedrooms, bathrooms, living rooms, and kitchens to detect the presence and activity of people. Door sensors were installed at specific doors and entrances within the house, such as the refrigerator, bathroom door, and front door, to track interactions related to daily activities. Environmental sensors continuously monitored the temperature and humidity of specific rooms. Wearable physiological monitoring devices recorded heart rate, calories, and steps. Finally, sleep tracking mat placed under the mattress monitored sleep-related activities, including bed occupancy, breathing signals, and different sleep states. Figure 4 shows the one instance of each sensor type that is used to collect data.

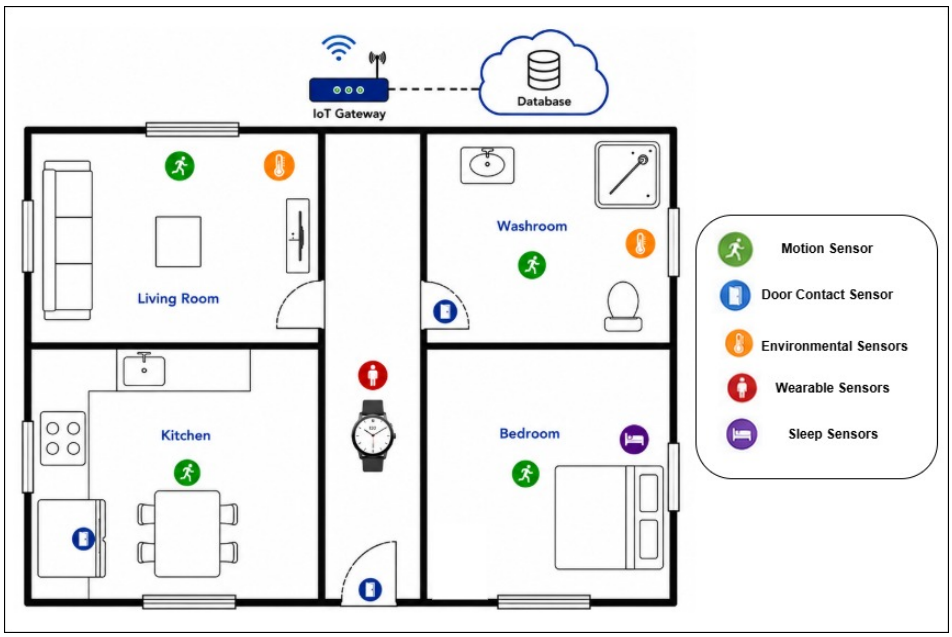

Figure 3. Home layout with sensor placement.

Figure 4. Sensors used to collect the data.

3.2. Data Acquisition and Timestamp Standardization

Throughout the monitoring period, the sensing infrastructure continuously generates event-related observational data with timestamps. Sensor data is acquired asynchronously based on changes in environmental conditions, participant movement, physiological activity, or specific sensor behaviors. Sensor data is transmitted via gateway-based local communication infrastructure and then stored in a cloud-based digital repository for subsequent processing and analysis as shown in Figure 5. The temporal density of the observation data varies depending on the sensing method, as different sensing devices operate at different sampling rates and triggering conditions.

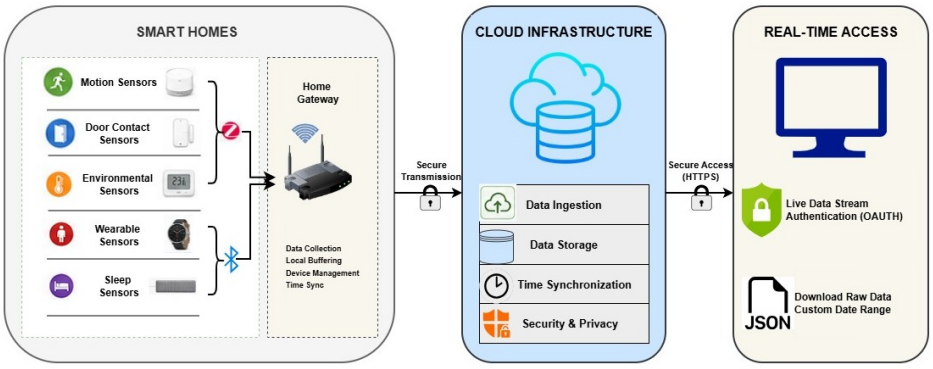

Figure 5. Data collection architecture.

Available timestamps from the different sensor streams were converted to UTC during preprocessing. This conversion provides a common time representation across participants and sensing modalities but does not, by itself, demonstrate that the internal clocks of all sensing devices were synchronized. Device-level clock synchronization and clock drift were not independently assessed, and no temporal offsets were estimated or corrected during preprocessing. In addition, delays may have occurred while observations were transmitted from the sensing devices through the local gateway to the cloud platform. Therefore, the dataset should be described as having timestamps standardized to UTC rather than as being fully time-synchronized.

3.3. Data Preprocessing and Cleaning

Sensor data is collected and stored in JSON format as a timestamped event stream generated by heterogeneous sensing devices. Each JSON record contains information such

as a timestamp, anonymous participant ID, sensor and gateway IDs, measurement category, and corresponding sensor value. During preprocessing, a Python preprocessing script parses the JSON records and converts them to CSV format. The nested data structure is flattened into a standardized tabular representation with uniform columns for storing timestamps, users, sensor IDs, measurement types, and sensor values. The timestamp field for all sensing modes is converted to a standardized UTC date and time representation to provide a common timestamp representation across devices and participants.

After conversion, sensor identifiers and measurement labels were standardized to unify the naming conventions across the entire dataset. Observational data from different detection methods (motion, contact, and environmental sensors, wearable physiological monitoring devices, and sleep monitoring systems) were then merged into a unified tabular structure, preserving their original timestamps and sensor associations. Because the detection infrastructure employs an event-driven acquisition strategy, different sensor methods generate observational data at varying frequencies based on participant activity and environmental conditions. Consequently, physiological and sleep monitoring devices generate relatively dense, continuous data streams, while motion and contact sensors generate sparse, asynchronous, event-driven observational data.

3.4. Data Validation

Data quality was evaluated separately for each participant and sensor stream. The validation examined whether each expected sensor was present, the first and last observation times, the number of observations, the number of active recording days, prolonged interruptions, exact duplicate rows, malformed records, and invalid timestamps. Expected monitoring duration was obtained from the participant metadata, whereas actual data availability was determined from the timestamps contained in the participant CSV files.

Empty fields within a valid Withings record were not classified as missing sensor data. The Withings export may provide a value for one measurement, such as heart rate, while the corresponding steps or calories fields are empty at the same timestamp. In these cases, the device produced a valid observation, and at least one measurement was available. Missing or unavailable data were instead defined at the sensor-stream level: an expected sensor was considered unavailable when it was entirely absent, stopped reporting before the end of the observation period, or showed a prolonged interruption relative to its usual reporting pattern. For event-driven motion and door contact sensors, low event counts alone were not considered evidence of missing data because a lack of events may reflect genuine inactivity. Complete absence and prolonged interruptions were assessed in relation to the other sensors installed in the same residence.

The validation identified several participant-specific availability issues. For user1, no observations were available from `doorcontact1` during the monitoring period. For user4, `doorcontact2` contained an interruption of approximately 11 days, and the `temp1` environmental stream contained an interruption of approximately 2.2 days. For user5, the `WithingsSleepRaw` stream ended on 24 November 2025, before the end of the monitoring period, and sleep data were available for 18 nights. In contrast, all installed sensor streams for users6-user10 were represented on every available dataset day. Wearable-data days and available sleep monitoring nights were reported as data-availability indicators and should not be interpreted as verified device adherence.

The normalized participant files contained 1,033,970 timestamp-valid observations. A total of 1654 exact duplicate rows were identified, while no malformed normalized rows or invalid timestamps were detected. The duplicate rows were retained in the distributed files and are documented by the accompanying validation code. No interpolation, synthetic

padding, or resampling was performed to replace unavailable periods. Participant-level availability and quality results are summarized in Table 4.

Table 4. Participant-level data availability and quality based on sensor-stream presence and interruptions.

ID	Expected Days	Actual Span (d)	Records	Duplicates	Observed Unavailable or Interrupted Stream	Wearable Data Days	Sleep Nights
user1	34	34.0	91,218	82	`doorcontact1` absent for the complete monitoring period	34	35
user2	33	34.0	90,668	39	No ambient-sensor interruption identified; wearable stream ended approximately 3 days before the other streams	31	34
user3	33	33.4	159,128	417	Wearable stream ended on 27 November; one sleep-stream interruption of approximately 40.5 h	22	32
user4	33	34.0	96,799	104	`doorcontact2`: approximately 11-day interruption; `temp1`: approximately 2.2-day interruption	32	34
user5	33	33.6	155,024	264	Sleep stream ended on 24 November	34	18
user6	28	27.4	99,607	199	No unavailable sensor stream identified within the recorded period	28	28
user7	29	28.6	70,210	158	No unavailable sensor stream identified within the recorded period	29	29
user8	29	28.6	89,802	147	No unavailable sensor stream identified within the recorded period	29	29
user9	28	27.6	71,306	109	No unavailable sensor stream identified within the recorded period	28	28
user10	27	27.1	110,208	135	No unavailable sensor stream identified within the recorded period	28	28

Notes: Expected days are the monitoring durations reported in the participant metadata. Actual span is the interval between the first and last observations in each participant file. Records occurring outside the stated metadata dates were retained, which explains why the number of wearable-data days or sleep nights may occasionally exceed the expected duration. An unavailable stream was identified when an expected sensor was entirely absent, stopped reporting before the other sensors, or contained a prolonged interruption relative to its usual reporting pattern. Empty fields within a valid Withings event were not classified as missing observations because another measurement was available at the same timestamp. Sleep nights were counted when the sleep-state stream contained at least one recorded sleep state during the corresponding night. Duplicate values are exact duplicate rows retained in the distributed CSV files. No malformed normalized rows or invalid timestamps were detected.

4. User Notes

This dataset is intended for academic and research use in data analysis related to smart homes, home assistance, homecare monitoring, behavioral analysis, human activity recognition, and longitudinal health sensor research. The published data preserves the original temporal structure and multimodal characteristics of real-world residential sensing environments, supporting downstream applications such as statistical analysis, machine learning, deep learning, time series modeling, and digital twin development. No independently annotated activity ground truth is included. Sensor outputs such as motion occupancy, door state, sleep state, and steps are device-derived observations rather than external activity labels. Consequently, the dataset directly supports unsupervised amd self-supervised modeling, routine-modeling, and anomaly-detection [5,10].

To improve accessibility and interoperability, the JSON event streams were converted to participant-level CSV files while preserving exported timestamps, sensor identifiers, measurement types, and values. Available timestamps were standardized to UTC; this common representation does not demonstrate device-level clock synchronization. No interpolation, synthetic padding, or resampling was performed. The distributed CSV files retain missing values and 1654 exact duplicate rows, which are identified by the accompanying validation code rather than silently removed. The preprocessing and validation code is deposited alongside the dataset. It validates the five-column schema, parses UTC times-

tamps, identifies empty measurement fields and stream-level availability interruptions, quantifies temporal gaps, and generates participant and sensor-level quality tables without overwriting the released CSV files.

5. Conclusions

This dataset contributes longitudinal multimodal observations from real residences, combining ambient, environmental, wearable, and sleep sensing while preserving an asynchronous temporal structure and real-world missingness. The accompanying code and quality tables make duplicates, unavailable periods, temporal interruptions, and modality-specific coverage explicit. Reuse should account for heterogeneous home layouts, household attribution, device-dependent reporting, the absence of independently annotated activities, and the distinction between UTC standardization and device-clock synchronization.

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Institutional Review Board Statement: The study protocol was reviewed and approved by the Etikprövningsmyndigheten, under approval number 2025-01109-01-765245.

Informed Consent Statement: All participants signed informed consent forms before participation and were informed of the study's purpose and the types of data collected.

Data Availability Statement: For reasons of confidentiality and ethical considerations related to long-term residential monitoring, data is provided only upon reasonable request and for research and academic purposes only. Researchers, educational institutions, and non-commercial projects may obtain access after reviewing the intended use of the data. All published data is anonymized and does not contain any personally identifiable information.

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Conflicts of Interest: The authors declare no conflicts of interest.

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