Integrated technologies of care: proof-of-concept study on an integrated physiological and activity monitoring system to enhance independence and care

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ABSTRACT

This study presents a multi-sensor activity monitoring system designed to verify daily behaviours and detect physiological anomalies within a controlled home environment. Seven subjects participated in a scripted routine of Activities of Daily Living carried out in a home-like environment. The proposed system is designed for single-occupancy environments (e.g. individuals living alone). Accordingly, this proof-of-concept evaluation was conducted under controlled, single-participant conditions using sequential, non-concurrent activities and excluding overlapping sensor changes. Within the routine, different sensors capture physiological hydration levels and breathing rates of the participant as sensor events, to check whether the measurements were within normal levels. In addition, camera, contact, motion and pressure sensors are used to capture action triggered events within the routine. Sensor data is processed and translated into a time-ordered trace of events. A model is constructed to capture the layout of the controlled environment and the trace of events. Expected behaviours are specified as properties encoded in Linear Temporal Logic and model checking is used to assess whether the sensor-captured events align with these expectations. Through model checking, the captured behaviour can be verified against a set of logical formulae representing properties. The identified deviations from expected behaviours demonstrate the viable application of model checking in the verification of Activities of Daily Living. Cross-sensor data aggregation compensates for occasional sensor inaccuracy, ensuring reliability. The initial results support the system's potential for use in behaviour and physiological monitoring of people living independently, where accurate and unobtrusive monitoring is crucial.

Introduction

In recent years, the need for advanced care solutions has become increasingly urgent due to significant demographic changes worldwide. According to the World Health Organisation, the proportion of the global population aged 60 and above is projected to increase from 12% in 2015 to 22% in 2050[1]. This rapid growth of the ageing population is likely to put a strain on already burdened healthcare systems and on economic development[2]. To support this demographic change, care models must move from reactive to proactive through remote health monitoring, focusing on early interventions and prevention[3]. In this work, we introduce a multimodal sensor platform that integrates novel physiological sensors and commercially available motion, camera and contact sensors within a framework capable of personalisation. To identify unexpected behaviours we employ a model checker, a tool that verifies whether observed data satisfies a given formal property (see Subsection Model). This approach explores the combined potential of multiple sensing modalities and formal methods.

There is a growing trend in new technologies that capture or monitor different aspects of a person's health or activity. However, the diverse range of such technologies can be overwhelming for people, often requiring them to monitor data on separate platforms. Moreover, traditional care models often struggle to balance personalisation with scalability, particularly for populations requiring continuous monitoring of physiological parameters and activities. This is exacerbated by having a variety of unintegrated sensor systems that process data separately, resulting in a fractured, potentially inconsistent, understanding of individuals, their activities and environment. Given this context, advanced integrated systems that combine personalised physiological monitoring with activity tracking are emerging as transformative tools[4]. One promising area for advancing the care model with technology is through the use of "smart homes" that have sensors and computer models to help monitor

Activities of Daily Living (ADLs). ADLs are basic, essential self-care tasks that individuals perform to maintain their health and independence[5]. Smart homes consist of two main components: 1) sensors that capture data from the environment and 2) a computer model that processes the sensor data into meaningful information that is shown to end-users for decision making. Morita et al.[6], in a broad scoping review, emphasise that most existing smart home health monitoring efforts rely heavily on passive infrared motion sensors and face challenges such as multi-occupant differentiation, interoperability and privacy risks. So, although significant progress has been happening, there are persistent gaps: many systems rely on a narrow set of modalities, demand substantial computational resources, and often lack interpretable mechanisms to rigorously verify whether behaviours comply with expected routines.

Recent developments in smart home technologies highlight the growing ability to monitor both behavioural and physiological signals using diverse, often unobtrusive, sensor modalities. For example, Zhou et al.[7] introduced a flexible, pressure-sensitive system capable of capturing respiration and ballistocardiogram (BCG) data from seated individuals in real-time. While this approach utilises an unobtrusive method for capturing respiration, BCG data is found to be unreliable due to its high sensitivity to movements, such as a person shifting in their seat. In another study, Yang et al.[8] presented humidity-based sensors that detect respiratory patterns with high accuracy through machine learning, highlighting the potential of non-invasive behaviour recognition in smart home contexts; however, this sensor is wearable and may not be practical for older people to use continuously in their daily lives. Li et al.[9] proposed a low-cost, AI-assisted wearable sensor system that captures multiple respiratory parameters such as breathing rate and the apnea–hypopnea index for real-time health diagnostics, while Srikrishnarka et al.[10] reviewed wearable technologies that non-invasively monitor metabolites in sweat, breath, and tears. Although wearable sensors offer the advantage of body-worn monitoring, research shows that older adults often harbour concerns – e.g. around usability, comfort, privacy and trust – that make them less inclined to adopt such technologies compared to more familiar or non-wearable alternatives[11]. Furthermore, reliance on wearable devices poses challenges, as older individuals must remember to put them on (after removal). Radio frequency (RF)-based sensors are emerging as a reliable and promising non-invasive technology for remote health monitoring that is capable of capturing health parameters, such as breathing rates and blood flow[12–16]. Due to their compact and low-profile design and size, these RF-based sensors can help to preserve privacy, and their unobtrusive and non-contact nature does not restrict the movement or ADLs of the individual being monitored. Camera-based monitoring systems have also long been investigated as a way to support older adults in living independently, with the literature consistently emphasising their practical benefits. Kim et al.[17], for example, recently proposed a camera-based setup that enables long-term detection of health-risk behaviours, such as inactivity, social isolation, and self-neglect, demonstrating high accuracy in predicting depression and cognitive decline through action recognition. However, a recent scoping review of camera-based Ambient Assisted Living technologies also identifies privacy concerns as a major barrier to acceptance among older adults[18]. In response to these concerns, innovative approaches are emerging. Wang et al.[19], for instance, describe an AI-driven camera system that preserves privacy by replacing people in the video with avatars using pose estimation and anonymisation, while still detecting falls. Such methods often aim to strike a balance between monitoring utility, personal dignity and privacy.

Physiological sensors such as wearables often suffer from inaccuracies caused by movement artefacts or poor contact, and the lack of calibration and ground truth data makes it difficult to validate their outputs reliably. Similarly, contact and motion sensors may produce ambiguous or noisy data. However, the most important challenge for current sensors is that when used in isolation, they are more susceptible to providing incomplete, or even incorrect, insights as they miss out on signals that other sensors could provide. In contrast, using a multimodal sensor approach allows different sensing modalities to complement each other, while offering benefits like redundancy, increased reliability, and the ability to capture diverse aspects of the environment and activities.

In parallel to current sensors used in smart home, machine learning algorithms are increasingly being used for activity recognition. Zolfaghari et al.[20], for instance, developed an image-based, deep learning method that processes ambient sensor streams into trajectory maps, enabling unobtrusive detection of ADLs without the need for cameras or wearables. Das et al.[21] complement this trend by introducing an explainable activity recognition framework that generates natural language explanations for detected behaviours using SHAP[22], a game-theoretic approach that computes Shapley values to quantify each feature's (i.e., sensor event's) marginal contribution to a model's prediction. While many approaches rely on machine learning methods for pattern recognition, other research focuses specifically on identifying behavioural anomalies and deviations. For instance, Dahmen et al.[23] introduced activity-aware models for security monitoring in smart homes, while Cook et al.[24] used machine learning techniques to quantify changes in behaviour. A smaller body of research has explored formal frameworks for behaviour verification. For example, Magherini et al.[25] applied temporal logic and model checking to ambient-assisted living scenarios, offering runtime verification of human activities; however, these formal applications have remained limited in modality coverage and scope.

Our study positions itself within this landscape as a controlled environment proof-of-concept, consistent with the validation approaches of many previous efforts. While the study does not yet capture the full complexity and variability of real-home environments, it still makes several distinct contributions. We leverage the advantages of a multimodal sensing approach by integrating new sensor technologies that measure physiological parameters with commercially available sensors and cameras for understanding behavioural patterns into a framework that allows for personalisation and enhances overall sensing accuracy of various parameters and reliability of the monitoring system. By integrating a wider array of unobtrusive sensors, including hydration, breathing, motion, pressure, contact, and camera, we reduce the reliance on any single modality and provide greater robustness against sensor failure. Our approach also leverages low-cost sensors embedded within everyday fixtures, suggesting potential for future scalable deployment, although further validation in real-world environments is required.

Importantly, we incorporate a formal framework that encodes expected behaviours in Linear Temporal Logic (LTL) and enables the application of model checking to the sensor-derived event traces. Although our study is conducted in a controlled environment, we have conducted an initial real-world study, installing subsets of our sensors for short periods in the homes of older adults to capture behavioural data[26]. Preliminary results suggest that the system is adaptable to real-world settings, although these findings require further evaluation. The current study provides a preliminary basis for exploring future, full-scale deployments of integrated sensors for activity and physiological monitoring in the homes of people living independently.

Aim

This work develops a multi-sensor monitoring system to assess the observed behaviour of an individual in a controlled environment. It is a proof-of-concept that integrates a unique combination of lab-developed and commercial sensors for unobtrusive physiological and activity monitoring, and uses formal verification to evaluate whether observed activities align with expected properties of ADLs. By integrating diverse sensing modalities – hydration, breathing, pressure, camera and motion sensors – and translating raw data into verifiable behavioural traces, the system has the potential to support reliable, unobtrusive monitoring for older adults living independently in future real-home deployments. In particular, by combining measurements of physiological parameters (such as hydration levels) with discrete events (like door opening) we can verify the behaviour of a subject against a set of predefined properties.

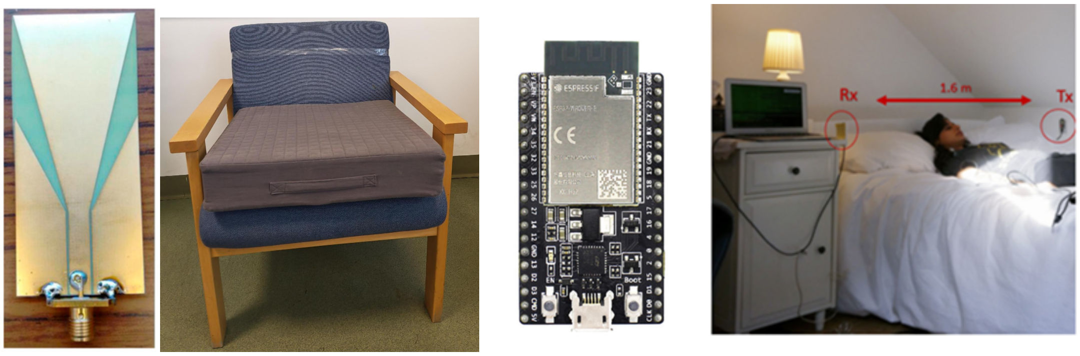
Overview of Sensors in Integrated Physiological and Activities Monitoring System

This section discusses the sensors that were installed and used to capture data in our Integrated Sensing Lab environment. The work was done as part of the Advanced Care Research Centre (ACRC)[27] at the University of Edinburgh, a multidisciplinary research programme that integrates social science, medicine, healthcare, engineering, informatics and data science[28].

Physiological Sensors

We first introduce the radiofrequency-based, physiological sensors developed in our lab and used for capturing hydration and breathing rates.

Hydration Sensor. Body hydration levels are measured using RF sensing embedded in a cushion that the person sits on. The hydration measuring device is a novel invention that was developed by researchers in the ACRC[29]. The RF sensors used for capturing hydration changes in the body are ultra-wideband (UWB) rectangular planar monopole antennas. The antenna is a modified design of a sensor developed in some of our previous work[30] and has a 0.2 mm thick FR-4 substrate, commonly used for printed circuit boards (PCBs). This material is chosen due to its strong structure, high insulation, minimum interference and water resistance. For measuring hydration inside the subject's body non-invasively, only the near field regions of the antenna are investigated because far field ones are at a much larger distance than needed for this application. There are two near field regions: 1) Reactive Near Field, and 2) Radiating Near Field (i.e. Fresnel Region[31]). For this study, we focus on the Fresnel Region as it is the area that is in close proximity to the antenna sensors (i.e. the person's body). Since the Fresnel region consists of radiating waves, it is assumed that the reflected RF waves captured by the antenna arise from a region in close proximity to the sensor, and can be expressed as the reflection coefficient (or S11), which is a parameter that describes how much RF waves is reflected by an impedance discontinuity in the transmission medium. In this case, the transmission medium is the subject sitting on the cushion housing the antenna sensors shown in Figure 1b. A cushion was deemed to be an appropriate piece of furniture that a person can sit on comfortably during times when hydration is measured based on recommendations from our Patient and Public Involvement and Engagement (PPIE) network[3] (see the end of this section). Four RF sensors were installed inside the cushion with dimensions 45 cm by 45 cm. A cut is made in the cushion in order to place the sensors inside and allow the wires to come out and connect to a host computer containing software to control the RF signals generated by the sensors and capture measurements accordingly. Finally, we note that, based on our design optimisation, a frequency band between 0.8 GHz to 2.5 GHz was chosen. This ensures that the antenna can detect changes in hydration within the subject's body without noise. Thus, for the hydration sensor, a threshold value is applied during post-processing to assess whether the hydration level of the subject falls within normal range. In particular, the hydration sensor is sensitive enough to detect changes in hydration levels even as ingested water passes through the oesophagus, allowing near-immediate detection of water intake. In our previous data analysis[29] we observed that the average S11 value of the RF sensor on a human body is -22.5



(a) (b) (c) (d)

Figure 1. Physiological sensors installed in the Integrated Sensing Lab: (a) Example of fabricated RF sensor used for hydration measurement,(b) Hydration measurement device which is a seat cushion that contains four RF sensors placed inside, (c) Sensor used to capture breathing rates (ESP32-DevKitC-VE), (d) Example of subject being monitored for breathing

dB and found that when a person is dehydrated, the S11 value shifts upwards, indicating a lower conductivity in the body. Conversely, when the amount of water in a person's body increases, the S11 value shifts downwards, signifying a higher loss in RF waves due to higher conductivity inside the body. For this study, we thus set the S11 threshold value to be at -22.5 dB, with a value above this threshold indicating that the person is *dehydrated*. In addition, we also consider overhydration, where a person has a high water content in their body. This is also undesirable as it may lead to a person drinking more fluid than their kidneys can excrete, potentially resulting in dilutional hyponatremia, where the blood's sodium concentration becomes dangerously low and affects mobility[32]. When overhydration occurs, the S11 value decreases further because the person's body will have a higher dielectric constant and thus increases the loss in the propagated RF waves from the sensor. For this study, based on the data from our previous work[29], we set a threshold value of -75 dB for overhydration. We note that the S11 threshold values used in this study were empirically derived from the experimental dataset obtained during our previous controlled measurements and data analysis. More specifically, this earlier study[29] investigated changes in S11 by monitoring participants under controlled hydration conditions involving water intake volumes of 250 mL, 500 mL, and 750 mL. To establish a baseline dehydration condition, participants fasted the day before testing and an initial measurement was taken prior to any water consumption (0 mL intake). The average S11 value obtained from this condition was used as the dehydration reference point. These threshold values were selected to demonstrate distinguishable RF response trends associated with hydration-related physiological changes observed within the experimental dataset. However, they should not be interpreted as universal clinical hydration thresholds, since inter-subject variability, such as body composition or clothing worn, may influence these measurements. As such, subject-specific calibration is required. Some of our ongoing work is focused on validating and refining these thresholds using established clinical hydration assessment techniques.

Breathing Sensor. Breathing rates are measured by changes in Wi-Fi RF signal amplitudes caused by the presence of a person between the transmitter and receiver. For measuring breathing rates, two ESP32 Microcontroller Development Kits (ESP32-DevKitC-VE) – one of them shown in Figure 1c – are used as Wi-Fi antennas, where one acts as a transmitter (TX) and the other as a receiver (RX). The variations in the Channel State Information (CSI) amplitude collected at the RX is preprocessed to measure the respiration rate (RR). The development kit includes a built-in PCB omnidirectional antenna, operating in the 2.4 GHz band, which is used to transmit and receive Wi-Fi packets that include CSI data for channel estimation. Figure 1d shows the kits placed at a bedside.

The fundamental principles of Wi-Fi unobtrusive sensing rely on the channel estimation procedure of the IEEE 802.11n communication protocol. CSI Wi-Fi describes the propagation of the signal through the channel between the TX and RX, effectively describing environmental effects, such as scattering and fading, as well as dynamic changes in the channel, including body movements. Access to CSI data enables more sensitive Wi-Fi sensing in a wider range compared to previous work that relies on Wi-Fi Received Signal Strength Indicator (RSSI) data, which itself often depends on proximity to Line of Sight (LOS)[33]. CSI data from Wi-Fi sensors thus overcomes some of the limits of prior approaches for unobtrusive monitoring.

For measuring the breathing data, we first identified the respiration rate to use in the experiments. For adults, we found that the respiration rate at rest falls within the 12 to 18 BPM range[34]. Since the breathing rates are guided by a metronome, these thresholds are lowered to be between 11 and 16 BPM to avoid the extremes and ensure that the breathing rates are not too difficult for the participants to sustain for the test duration.

Additional information regarding the physiological sensors and their measurement ranges can be found in the Appendix II:

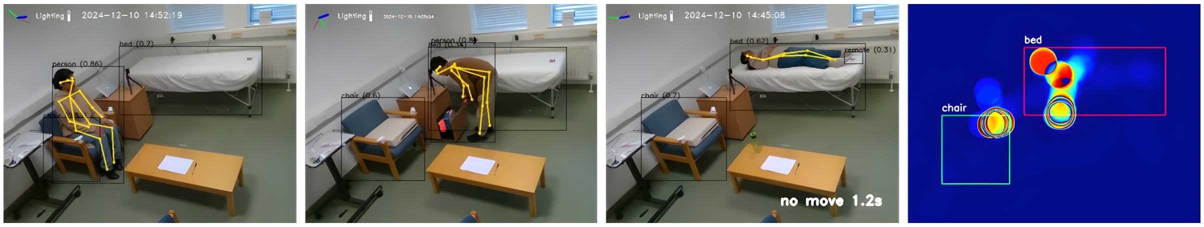


Figure 2. Example of human motion detection and activity recognition using the computer vision system[40]. The first three images show the detection of the person sitting on the chair, standing, and lying on the bed, respectively, with pose estimation and object bounding boxes overlaid. The fourth image shows the accumulated heatmap of movement activity over time, highlighting key areas such as the chair and bed. Only critical events, such as the timestamps when the person enters or exits the room and when the person sits on the chair or lies on the bed, are recorded as text to ensure privacy.

Individual Sensor Results.

Pressure Sensor

The pressure sensor is used to detect whether a person is sitting on a cushion based on the change in pressure detected via the sensor's resistance[35]. The system consists of a 3×3 piezoresistive sensor matrix (i.e. total of nine sensor elements) and an Arduino microcontroller. This matrix is embedded within a cushion to detect the movement-related state of the person sitting on it. When a person sits on the cushion, each piezoresistive sensor generates electrical signals of varying amplitudes based on the pressure at their respective positions. The Arduino board processes these signals to compute a numerical value representing the movement intensity of the person[36]. When no one is sitting on the cushion, the sensors experience little to no pressure, except for the minor force exerted by the cushion itself, and the system broadcasts a “No Person” result to the computer. When the subject is still, the pressure on each sensor remains constant, and the system displays a value of zero. During minor movements, such as adjusting one's sitting posture, and large movements like standing up or sitting down, the system outputs different values depending on the magnitude of the movement.

Contact and Motion Sensors

We next briefly describe our contact and motion sensors. These are off-the-shelf, commercially-available devices complementing the bespoke ones described above.

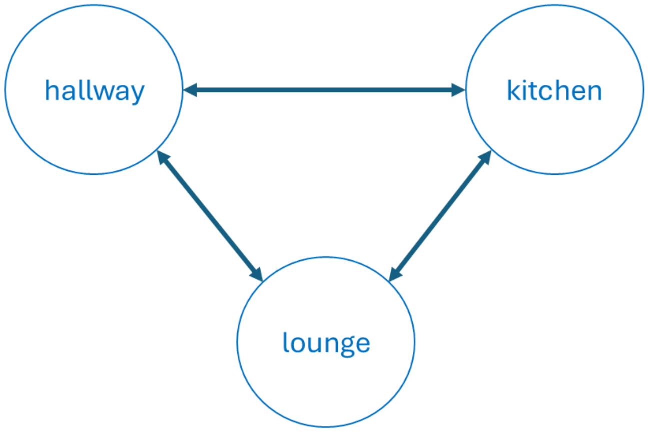
Contact sensors. These are used to detect the opening and closing of doors and consist of two parts: the main body and the magnet. The sensor broadcasts its state, *closed* or *opened*, every time the two parts of the sensor are within 8 mm of each other or more than 8 mm apart, respectively.

Motion sensors. These devices detect movement within the area which they monitor. Each uses a passive infrared sensor to detect movement, with a detection angle of 150° and a range of up to 7 metres. A motion sensor has two possible states: *clear* and *detected*. If motion is registered, while the sensor is in a *clear* state, the sensor broadcasts a *detected* state. The sensor switches back to a *clear* state after 30 seconds of inactivity (i.e. no motion detected).

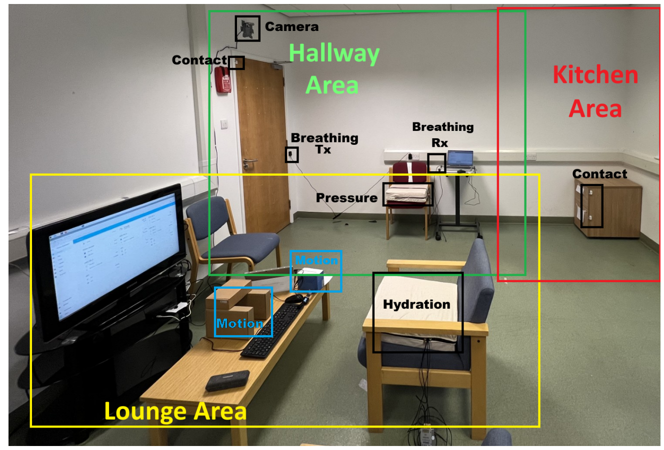
These sensors are compatible with Zigbee-based systems[37] and we use a Phoscon II BEE gateway to control and manage them. This part of the sensor platform consists of two key components: the integration and management of various sensors through an open source home automation platform, Home Assistant[38], and the storage and management of the data collected by these sensors. For data storage, we rely on an open-source time-series database, InfluxDB[39], which is optimised to handle large volumes of time-series data, ensuring efficient data storage and retrieval. A Raspberry Pi 4 serves as the central hub for the setup of the contact and motion sensors. It runs both the home automation platform and InfluxDB, and is connected to the USB gateway for Zigbee device communication.

Camera Sensor

This sensor complements non-visual monitoring by capturing high-level semantic information. For example, visual data can determine whether a person is present, how many individuals are in the area, their locations, movement trajectories, postures, and the presence of objects. We use an Intel RealSense D415 RGB-D camera[41] to capture both depth and colour images for analysis, with depth data acquired through infrared sensing, enabling operation in low-light environments. A Jetson Nano[42] processes these images in real-time. Computer vision algorithms[40] are employed to detect the presence of humans and objects, as well as identify 2D joint locations of the subject, at a rate of approximately 7 to 8 frames per second. An example is illustrated in Figure 2. The direction of human motion is estimated from the detected body region, and the speed of 2D body movements is measured with a precision of up to 2.4 pixels root mean square error (RMSE) per frame[43]. To ensure privacy,



(a) Graph representation of the lab, where each node corresponds to a different area and all nodes are interconnected.



(b) Photograph of the lab, showing the actual setup, location of sensors, and arrangement of the space.

Figure 3. Overview of the lab setup, including a graphical layout and photograph of the actual space.

only anonymous critical events are logged as text (e.g. timestamps of room entry and exit). All video and image data are locally processed in real-time on the Jetson Nano to extract these events and are then deleted.

The protocols for deployment of all the sensors mentioned in this section were co-developed with feedback from the ACRC's PPIE group. This consists of members of the public and carers of older adults who have experience of health and social care, and are interested in how we can use technology and data to improve healthcare[3].

Integrated Sensing Lab: Environment, Properties and Model

This section describes the sensing lab in terms of its locations and installed sensors, and outline the five properties later used in the Experiments section. We then present the symbolic model of the environment and illustrate how similarly structured representations can accommodate different sensor types, showing the adaptability of our model. Finally, we describe how the raw outputs from the various sensors are integrated into this symbolic model.

Overview of the Integrated Sensing Lab

Our sensing lab aims to simulate spaces commonly found in a home environment and consists of three different areas: i) the entrance *hallway* that gives access to the living space, ii) a *lounge* area that provides a space for people to relax, and iii) a *kitchen* area with essential appliances for food preparation and storage. The areas are connected to each other and can be represented as the graph in Figure 3a. As shown in Figure 3b, relevant objects that can be found in most living spaces (e.g. TV and armchair in the lounge and a refrigerator in the kitchen) are placed in each area. The proof-of-concept evaluation presented in this study was conducted under controlled, single-participant conditions mirroring replaced*real-world*real-world situations where an individual lives alone. In the evaluation we scripted sequential activities. Technically, simultaneous sensor triggers are implicitly linearised based on their arrival order in the database; therefore, scenarios involving complex concurrent activities or overlapping simultaneous sensor changes are outside the scope of the present study. We now describe the sensors installed in the different areas:

- The hallway consists of i) a camera sensor positioned on top of the door (entrance), ii) a contact sensor on the door, iii) a pressure sensor positioned on the chair next to the door, iv) a breathing sensor next to the chair with the pressure sensor, and v) a motion sensor that registers any movement in the hallway.
- The kitchen consists of i) a motion sensor that registers any movement in the kitchen and ii) two contact sensors: one on the door of the cupboard containing glasses and another on the door of a refrigerator.
- The lounge area consists of i) a motion sensor that registers any movement in the lounge and ii) a hydration sensor positioned on the armchair in front of the TV.

Note that, although there were no internal room dividers, i.e. the subject is able to move freely within the lab, each motion sensor was positioned so it would only register movement within a specific area. Altogether, the sensors were placed to capture

Table 1. List of the sensors deployed in the lab depicted in Figure 3b

Sensor Type	Lab Area	Fixture	Name
Contact	hallway	Door	door
Camera	hallway	Door	camera
Motion	hallway	Facing pressure cushion	motionHallway
Contact	kitchen	Refrigerator door	refrigerator
Contact	kitchen	Cupboard	cupboard
Motion	kitchen	On refrigerator	motionKitchen
Hydration	lounge	Hydration cushion	hydration
Breathing	hallway	Facing pressure cushion	breathing
Pressure	hallway	Pressure cushion	cushion
Motion	lounge	Facing hydration cushion	motionLounge

events associated with typical indoor activities of an individual. For example, a person sitting on the armchair in front of the TV would trigger the hydration sensor to measure their hydration level, while any movement (e.g. when the person sits on the armchair) is captured by the motion sensor. To capture whether a person is in the home environment, we use a combination of the camera sensor on the door of the hallway, the contact sensors on the door and the motion sensor in the hallway area. Table 1 presents the list of deployed sensors, including their type, location in the lab, fixture and name in the model (see Subsection Model). The next section describes the properties against which we check our model and explains how these checks provide decision support for reasoning about ADLs with the model.

Properties

The properties investigated in our scenarios fall into three categories: physiological safety, general safety guidelines and sensor operations. As mentioned previously, we specify them in Linear Temporal Logic[44] and then verify whether they hold for our model.

Physiological safety when leaving the home

We use our hydration sensor to test the physiological state of the subject prior to any excursion (captured by the camera sensor), since there are increased risks associated with going out when not well hydrated.

- Property 1: When a person leaves the home, their hydration level must have been observed to be within the normal range prior to leaving.

A more comprehensive version of the previous property adds the requirement that normal breathing (captured by the breathing sensor) is also confirmed.

- Property 2: When a person leaves the home, both their hydration and breathing must have been observed to be within the normal range prior to leaving.

These properties ensure that when the person leaves the home, they are in a normal physiological state, with the second one imposing a stricter constraint. However, we should acknowledge that these properties assume that the hydration measurements obtained prior to leaving remain representative of the subject's hydration state until they actually leave. However, this is a realistic assumption, as hydration levels are unlikely to change significantly over a short duration unless additional water is consumed.

Safety guidelines

Some properties are derived from general home safety recommendations, which capture behaviours that help reduce risks during daily activities. In this context, a contact sensor on the refrigerator door, combined with all sensors in the hallway and lounge, enables the detection of situations in which the refrigerator door is left open while the person is not in the kitchen.

- Property 3: Whenever the refrigerator door is open, the person must remain in the kitchen until the refrigerator door is closed.

Similarly, for safety reasons, it is recommended that people remove their outdoor footwear after entering the home[45]. Monitoring this involves a contact sensor on the entrance door, a motion sensor in the hallway and a pressure sensor on a cushion next to the entrance.

- Property 4: When a person enters the home they sit down on the stool, which is used as a proxy indicator that they may be taking off their shoes.

Note that the use of a cushion with a pressure sensor serves as a proxy for footwear removal, since directly verifying removal would need a sensor in the footwear itself. We consider the placement of the cushion near the entrance and the expectation that subjects concerned about this property may prefer to remove their footwear while sitting down as sufficient to make the cushion a reasonable proxy. We acknowledge, however, that sitting down does not necessarily imply footwear removal, and that some individuals may remove footwear without sitting. Therefore, this property should be interpreted as an approximate behavioural indicator rather than a direct confirmation of shoe removal.

Sensor cross-checking

To ensure reliable operation, sensors must provide consistent information. We focus on the action of a person entering the home and check that there is consistency between the sensors capturing this action (camera and contact sensors).

- Property 5: The camera detecting an entry must be preceded by the door opening and eventually followed by the door being closed again.

This property enforces consistency between the camera and door sensors, and ensures that a camera detecting someone entering is aligned with expected door activities (opening before the camera detects and entry and closing afterwards).

Together, these five chosen properties allow the system to verify not only the correct operation of sensors, but also that some important safety and health-related guidelines are being followed. A more detailed explanation of the properties and the formalism used to specify these properties, together with their exact logical formulations, is provided in Appendix I: Formalism and Property Specifications.

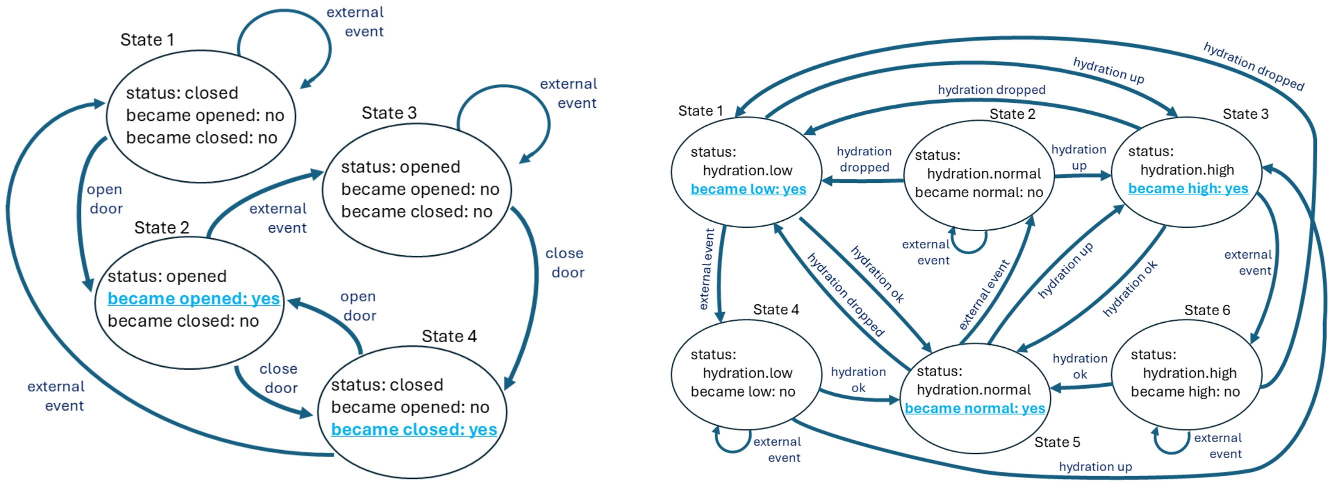
Model

We create a symbolic model that represents the data captured by sensors, allowing us to interrogate it using mathematical logic. The model is a finite state machine (FSM)[46] that provides a structured representation of the environment and of the ADL-related behaviour of a subject, as recorded by sensors. The FSM describes all the possible configurations a system can be in, called the states, and how the system transitions from one state to another in response to inputs. In our case, the inputs are signals from sensors. Note that we do not build the full FSM manually, but instead use the home layout and position of sensors within it to generate it automatically.

We start by representing each sensor as a small state machine, capturing its current state and whether it has changed states with respect to the last step. These state machines are then combined to model the whole environment and the subject's behaviour as captured through the sensors. This compositional approach makes the model easier to understand and maintain, allowing new sensors to be added with minimal effort. Our approach[47] uses the sensor and environment information to construct formal models in a systematic and automatic way.

Figure 4a shows a state machine for a contact sensor attached to a door. Each state represents the current status of the sensor (`opened`, `closed`) and whether it changed from its immediate previous status: became opened (`yes`, `no`) and became closed (`yes`, `no`). Thus, the state machine captures a single step of history. The arrows represent transitions related either to the contact sensor (close/open door) or to an external event unrelated to the sensor (e.g. motion in the hallway). In our model, a state change occurs whenever anything in the system changes. If the change is not caused by the sensor under consideration, we classify it as an external event. For example, state 1 represents the sensor being `closed` with `no` recent changes. From this state, the sensor can either remain `closed` (external event) or, through the door being opened, transition to state 2: status `opened` with the change noted (became opened `yes`). From state 2 the sensor can transition to two other states. First option is to remain `open` and transition to state 3: status `opened` and `no` recent changes. The other option is for it to transition, through the closing of the door, to state 4: status `closed` with the change noted (became closed `yes`). Similarly, from state 4 the sensor can transition to state 1 or state 2.

We use similar small state machines with one step of history to represent motion, camera, pressure, hydration and breathing sensors. Figure 4b, for example, depicts the state machine for the hydration sensor. The sensor can reach one of three different states when a measure is made: *low*, *normal* and *over* hydrated. In our model *low* hydration is represented by `hydration.low`, *normal* hydration is represented by `hydration.normal` and *over* hydration is represented by `hydration.high`. Note that some variables in some states, such as became normal and became high for state 1, are omitted to avoid cluttering the diagram in Figure 4b. The model ensures that only one hydration state is possible at any given time. A similar approach is applied to breathing; using `breathing.low`, `breathing.normal` and `breathing.high` to represent *low*, *normal* and *high* states.



(a) State machine for the contact sensor of a door

(b) State machine for the hydration sensor

Figure 4. State machines for two types of sensors

The behaviours of the motion, camera and pressure sensors are similar to that of the contact sensor. The motion sensor has two possible states, `motion.detected` or `motion.notDetected`, representing whether motion has been detected. The camera sensor detects whether a person is entering (`camera.entering`) or leaving (`camera.leaving`) the environment. The pressure sensor detects whether a subject is sitting on the cushion (`cushion.sitting`) or standing (`cushion.standing`).

A FSM that includes all sensors used in the model is not shown due to the large number of states involved. As an example of this complexity, Figure 5 shows a FSM that includes the sensors used in Property 5, namely the contact and the camera sensors. Note that, for the contact sensors, the state numbers in Figure 5 correspond to those shown in Figure 4a. The camera can be in a state of detecting a person (entering or leaving) or not detecting a person. The overall system state is defined by the joint condition of the two sensors, augmented with the one-step transition memory previously described. This results in a rapid increase in the number of states as additional sensors are incorporated. Note that the FSM allows for situations in which a person is recognised as entering or exiting while the door remains closed, while in practice a door would typically be open for a person to enter or leave, such situations may arise due to sensor noise or partial observations (e.g. a person appearing within the camera's field of view near a closed door). Rather than excluding these cases from the model, such situations can be detected using properties, enabling the cross-checking of sensor signals through the integration of multiple sensing modalities.

Figure 6 shows the placement of sensors across the three areas of our setup. In our model we specify the configuration of a group of sensors in a room as a combination of their current status values. This allows us to define the idea of a change in that group as simply a difference in that configuration between subsequent time steps. For example, grouping all sensors in the kitchen under the name *kitchen* allows us to access the *kitchen.change* variable.

Figure 7 shows an example of how the kitchen sensors can change over time. Motion detected in the kitchen at t_1 causes a change in the motion sensor (from no motion detected to motion detected). This change in the sensor state causes a change in the overall configuration of the kitchen sensors, i.e. a difference in states between t_0 and t_1, which is reflected in the value of *kitchen.change* at t_1. Then, when the refrigerator door in the kitchen is opened at t_2, the status of the sensor attached to the refrigerator door changes from `closed` to `opened` (meaning that *kitchen.change* stays true at t_2). This notion of room-level change enables a more concise expression of properties; for example, Property 3 uses it to monitor that no changes are observed in the hallway or the lounge while the refrigerator is open.

We make the modelling assumption that a person can only be in one place at a time; accordingly, the model is constructed so that all system states assign a person to exactly one location. Additionally, only one sensor can change at any particular time i.e. two sensors cannot change simultaneously. This ensures that the model accurately reflects the sequential nature of actions and sensor events within the environment.

We implement this model in NuSMV[48], a model checker that allows us to verify properties of the system. NuSMV can represent finite state systems and employs symbolic model checking to explore their state space. In this setting, a model consists of i) states, representing possible configurations during system execution, including sensor states and sensor events, ii) transitions, describing how the system evolves from one state to another, and iii) the initial conditions of the system. The model is verified against the properties previously described, which are logically-encoded (see Appendix I: Formalism and Property

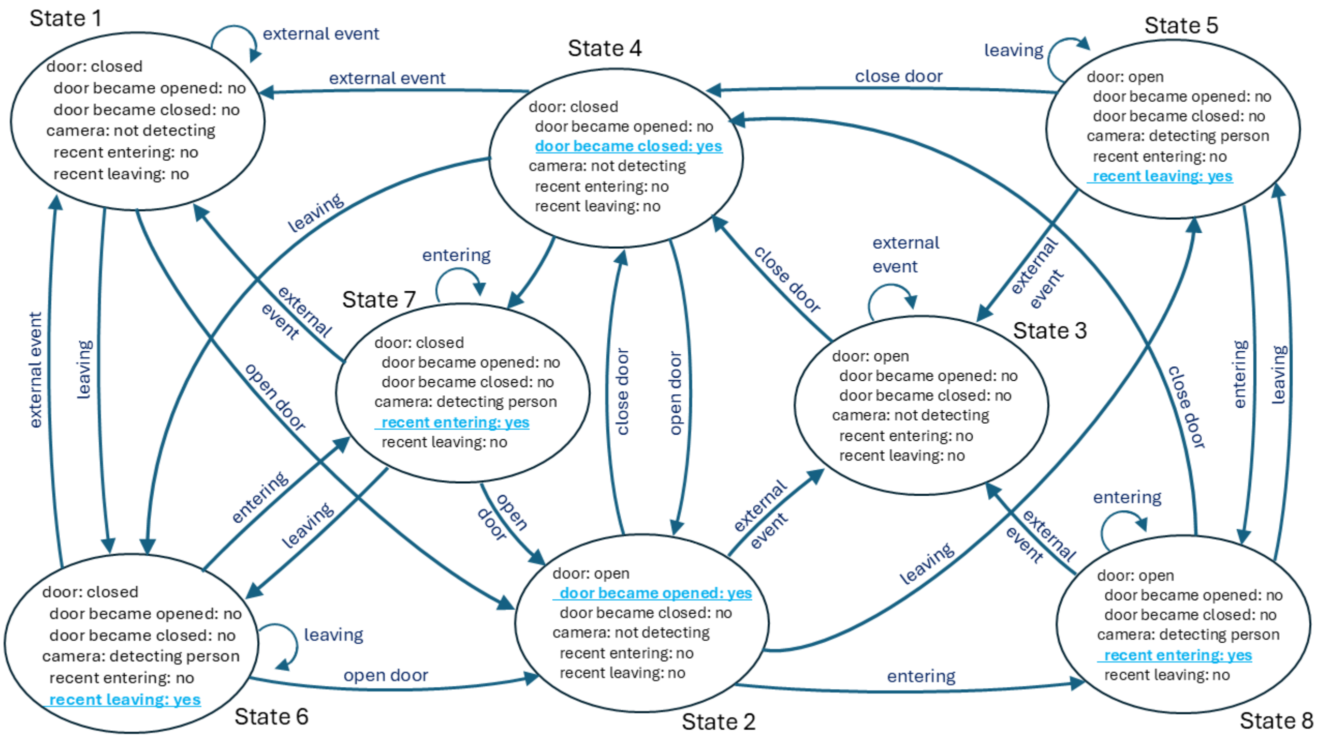


Figure 5. State machine for the contact and camera sensors used for Property 5

Specifications). If a property is violated, NuSMV generates a counter-example: a concrete sequence of states that illustrates where and how the violation occurs. A detailed discussion of NuSMV is beyond the scope of this paper, but we describe our underlying framework elsewhere[26,47].

Integration of Sensor Data

To ensure that the data captured from the various sensors can be incorporated into the model correctly, we discretise continuous measurements to boolean values. This is especially relevant for the physiological sensors (i.e. the hydration and breathing sensors) that capture data in an analog format which is processed to extract the associated physiological parameters.

For the hydration sensor data, we compare the measured S11 values of each subject with the threshold values mentioned in the section on Physiological Sensors. As a reminder, if the subject's measured S11 values are below -22.5 dB, then this indicates normal hydration. Otherwise, if S11 is above -22.5 dB, then the subject has low hydration. In addition, if S11 values are below -75 dB, then the subject has an abnormally high level of hydration. For Properties 1 and 2 we will check that the subject has a normal level of hydration, captured as the state `hydration.normal`. The transition into a normal hydration state is represented in the model by `hydration.ok`. If the subject has a low level of hydration, the transition into the state `hydration.low` is represented by `hydration.dropped`. If the subject has a high level of hydration, the transition to the state `hydration.high` is represented by `hydration.up`.

For the breathing sensor, if the respiratory rate is within the range 11 to 16 BPM, this corresponds to a `breathing.normal` state in our model (see the section on Physiological Sensors). The transition into a normal breathing state is represented in the model by `breathing.ok`. If the sensor detects a respiratory rate that is below 11 BPM, this corresponds to a `breathing.low` state, and the corresponding transition is represented by `breathing.dropped`. The detection of a respiratory rate greater than 16 BPM corresponds to a high breathing state, denoted by `breathing.excess`, and the corresponding transition is represented by `breathing.high`.

For the camera sensor, we translate the camera state to `camera.entering` when there is an observation within view of a subject opening the door and entering the room. Conversely, the camera state is marked as `camera.leaving` when the subject is observed moving toward the door from within the room, opening it and exiting. To check Properties 1 and 2, it is important that a `camera.leaving` signal is detected when the subject leaves the room. For Property 5, it is important to cross-check the camera and the door contact sensor based on the way the subject enters the home. For example, the subject may not fully close the door after entering or exiting the room, which can result in the camera detecting an event while the contact sensor remains open. In such instances, cross-checking the contact sensor and the camera events plays a crucial reliability role

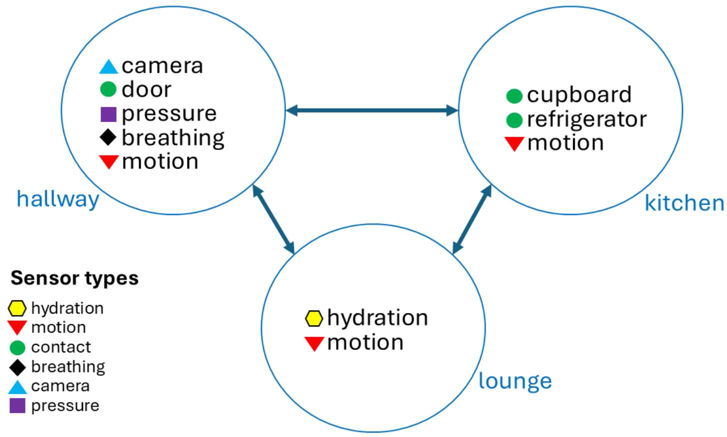


Figure 6. Distribution of the different sensors in the lab

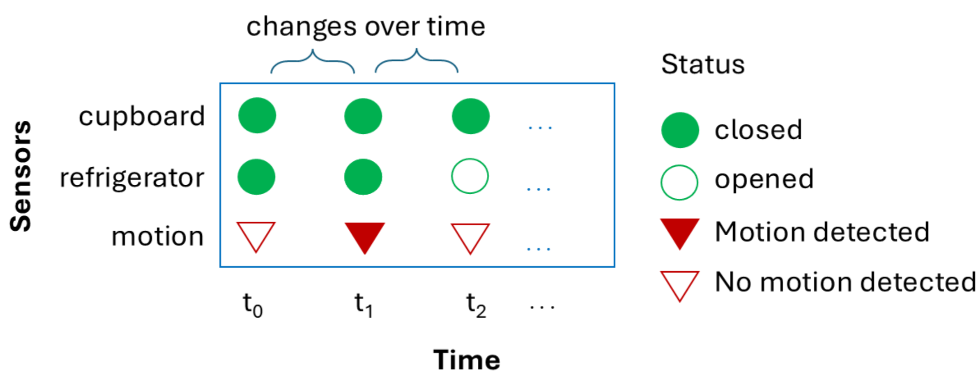


Figure 7. Changes in kitchen configuration between time markers t_0, t_1 and t_2

in confirming the actual event, i.e. whether a subject entered or left the room.

For the pressure sensor. we translate the cushion state to be `cushion.sitting` when there is an initial trigger of a subject sitting on the cushion. Conversely, the cushion state is marked as `cushion.standing` when there is an initial trigger of a subject standing from the cushion. In order to satisfy Property 4, it is important that after the subject closes the door in the hallway, they sit on the cushion. These actions should occur before the subject goes to the lounge or kitchen.

Finally, all processed sensor data, from both physiological and activity-based sensors, are consolidated into a unified dataset. This integration step involves aligning the outputs from multiple sensor modalities, each of which may differ in sampling frequency, data structure, and temporal granularity. For example, the hydration and breathing sensors output processed physiological state values at regular intervals, while motion, contact, camera, and pressure sensors often generate event-driven outputs triggered by specific actions or thresholds. To harmonise these sources, all data streams are synchronised based on their timestamps, and their corresponding boolean state representations are mapped to predefined state variables. This standardised format enables seamless interpretation by the model, which requires a consistent structure to validate logical and temporal properties related to user behaviour and health status.

Experiments

This study has ethical approval from the Ethics Committee of the School of Engineering at The University of Edinburgh. All experiments were carried out in accordance with the relevant guidelines and regulations. Informed consent was obtained from all subjects for both the study participation and the publication of identifying images in an online open-access publication. The study involved seven adult subjects, six of whom are authors of this work and one of whom was a PhD student not part of the authoring team or involved in the conduct of the work. Subjects were aged between 25 and 45 years. The cohort was a convenience sample and was not intended to be representative of a specific population e.g. older adults. The subjects conducted a set of behavioural actions that replicate common ADLs at home. The scenarios were developed by the authors to capture various sequences of events that can be formally checked to see whether the properties hold.

Prior to the experiment, participants were briefed on the procedure and the order of ADLs to be performed. The instructions were provided verbally, and participants were guided through the controlled environment to ensure understanding of the experimental procedure before commencing the scripted activities.

The experiments were designed around subject interactions and measurable physiological parameters that could be captured by the sensors. Consequently, behavioural premises were defined to ensure that subject activities generated interpretable event sequences. The main door was expected to be closed after entering and leaving the lab, consistent with expected behaviour in home environments. Likewise, as previously mentioned, the stool in the hallway was used as a proxy for people removing their shoes after entering the home and putting them back on before leaving. Similarly, the refrigerator door was expected to be closed after use and before leaving the kitchen area. Additionally, hydration was taken on the sofa in front of the TV, as this represents a common activity followed by most people, making this location ideal for the protocol.

The experiment is structured around a total of nine distinct instructions. While the sequence of instructions is given, the experiment permits the omission of specific steps. In particular, it is possible to skip instructions 2, 5, and 7; all other instructions must be executed. Table 2 shows the list of instructions in sequential order, which were mandatory and the sensors that captured data for each.

All experiments began with the same initial setup: all contact sensors were closed, and no sensor had been triggered prior to the participant entering the lab. There was no interference from other subjects during the experiments, all participants were outside the lab before starting and had low hydration level. The experiments consist of nine instructions carried out in a fixed sequence. Each participant enters the room, proceeds to the hallway and sits on a cushion to remove their shoes. The participant then moves to the lounge to take the first hydration measurement. Afterwards, the participant goes to the kitchen, opens the refrigerator and retrieves water. The participant returns to the lounge for the second hydration measurement, moves to the hallway to put their shoes back on, remains seated for two minutes, and subsequently exits the room.

Table 2. Instructions for the experiments, their mandatory status and their associated sensors.

Instructions	Mandatory	Contact	Motion	Camera	Breathing	Hydration	Pressure
1. Enter lab setup	*yes*	×	×	×			
2. Sit on hallway chair and take off shoes	*no*		×				×
3. Go to lounge and sit on hydration cushion	*yes*		×			×	
4. Go to kitchen	*yes*		×				
5. Get water from the refrigerator (drinking optional)	*no*	×	×				
6. Go to lounge and sit on hydration cushion	*yes*		×			×	
7. Go to hallway and sit on the hallway chair to put shoes back on	*no*		×				×
8. Sit (or remain seated) on the hallway chair for 2 minutes	*yes*		×		×		
9. Leave lab setup	*yes*	×	×	×			

During each instruction, sensors register or capture various physiological parameters and behavioural events. For the physiological sensors, some additional steps had to be taken for data capture. For instance, during the hydration measurements, each subject sits on the hydration cushion in the lounge area, and has their hydration level measured. An initial baseline hydration measurement is captured when the subject sits on the cushion after removing their shoes. The second hydration measurement is taken after the subject drank water in the kitchen. Similarly, during the breathing measurements, after the subject puts on their shoes in the hallway towards the end of the experiment, they need to sit for 2 minutes. This sitting period is needed to allow sufficient time for data capture. During that time, each subject is asked to breathe at a certain level (low, normal, or high) with the breathing sensor recording the data. The chosen breathing rate of the participants is controlled and acted on with the assistance of an audio guide, which is a metronome set at twice the breathing rate, such that the participants respond to alternate beats by inhaling or exhaling. Since the breathing rates are controlled, these thresholds are lowered to avoid both extremes and ensure that the breathing rates are not too difficult for the participants to sustain for the test duration. The overall time for a subject to complete the experiment ranges from 5 to 8 minutes.

In order to ensure randomness in the actions and validate the robustness of the model, each subject is asked to perform the exercise in different ways to vary the captured dataset. For example, each subject had different breathing rates, and some subjects left the refrigerator door open when retrieving water or did not drink the water. In some cases (see Table 3) subjects simply skipped the instructions. Subjects 2 and 7 did not sit on the cushion to take off their shoes after entering (step 2).

Similarly, subject 2 did not get water from the refrigerator (step 5). This variation in the experiments ensures that each subject's behaviour is individualistic and that all the captured measurements for each sensor are unique to the subject themselves.

We conducted seven experiments, one with each subject. Table 3 provides a breakdown of the instructions performed by the subjects during the experiments. For each experiment, we automatically created a model to verify our properties against the data collected. Table 4 shows the experiment time and the result for each property broken down by subject. The results are discussed in the next section.

Table 3. Instructions followed by each subject during the experiments.

Instructions	Subj 1	Subj 2	Subj 3	Subj 4	Subj 5	Subj 6	Subj 7
1. Enter lab setup	×	×	×	×	×	×	×
2. Sit on hallway chair and take off shoes		×	×	×	×	×	
3. Go to lounge and sit on hydration cushion	×	×	×	×	×	×	×
4. Go to kitchen	×	×	×	×	×	×	×
5. Get water from the refrigerator (drinking optional)	×		×	×	×	×	
6. Go to lounge and sit on hydration cushion	×	×	×	×	×	×	×
7. Go to hallway and sit on the hallway chair to put shoes back on	×	×	×	×	×	×	×
8. Sit (or remain seated) on the hallway chair for 2 minutes	×	×	×	×	×	×	×
9. Leave lab setup	×	×	×	×	×	×	×

Results

The main benefit of a symbolic model compared to directly analysing sensor data lies in its ability to systematically and automatically evaluate logical properties, and identify their violations. For each subject/experiment, sequences of events observed by the sensors are first incorporated into the symbolic model. Properties are then checked against this model rather than directly against the raw sensor data. A detailed technical explanation of this modelling approach can be found in one of our previous works[47]. The individual results for all sensors are provided in Appendix II: Individual Sensor Results.

Property Verification from Integrated Sensor Data

Figure 8 shows the events recorded by the various sensors during the experiments (see Table 2). The blue shading indicates the timing of the experiment for each subject (see also Table 4). The colours of the dots represent three general categories of events: movement (green) for motion sensors and camera, contact (blue) for door, cupboard, refrigerator and cushion, and physiological (orange) for hydration and breathing sensors. Events outside the blue shading, which were not included in the analysis, are omitted from the plot for clarity. In what follows, we present the results of checking whether our five properties are satisfied by our models.

Table 4 summarises the results of the experiments for each subject and property. Note that we found that a single sensing modality was insufficient to capture the nuances of ADLs. In what follows we discuss, for each property, the sensors involved and the significance of combining these sensors.

Hydration Before Leaving Home (Property 1)

Property 1 requires that a person's hydration level is normal prior to leaving the home.

Table 4. Property verification.

Subjects	Experiment Time	Property 1	Property 2	Property 3	Property 4	Property 5
Subject 1	11:29:57 - 11:34:20	Pass	Fail	Pass	Fail	Pass
Subject 2	11:36:44 - 11:40:19	Fail	Fail	Pass	Pass	Pass
Subject 3	11:41:34 - 11:45:24	Pass	no data	Pass	Pass	Pass
Subject 4	12:01:22 - 12:05:37	Pass	no data	Pass	Pass	Pass
Subject 5	12:07:45 - 12:11:58	Pass	Pass	Pass	Pass	Pass
Subject 6	12:14:07 - 12:18:05	Pass	Pass	Pass	Pass	Pass
Subject 7	12:19:40 - 12:23:08	Fail	Fail	Pass	Fail	Pass

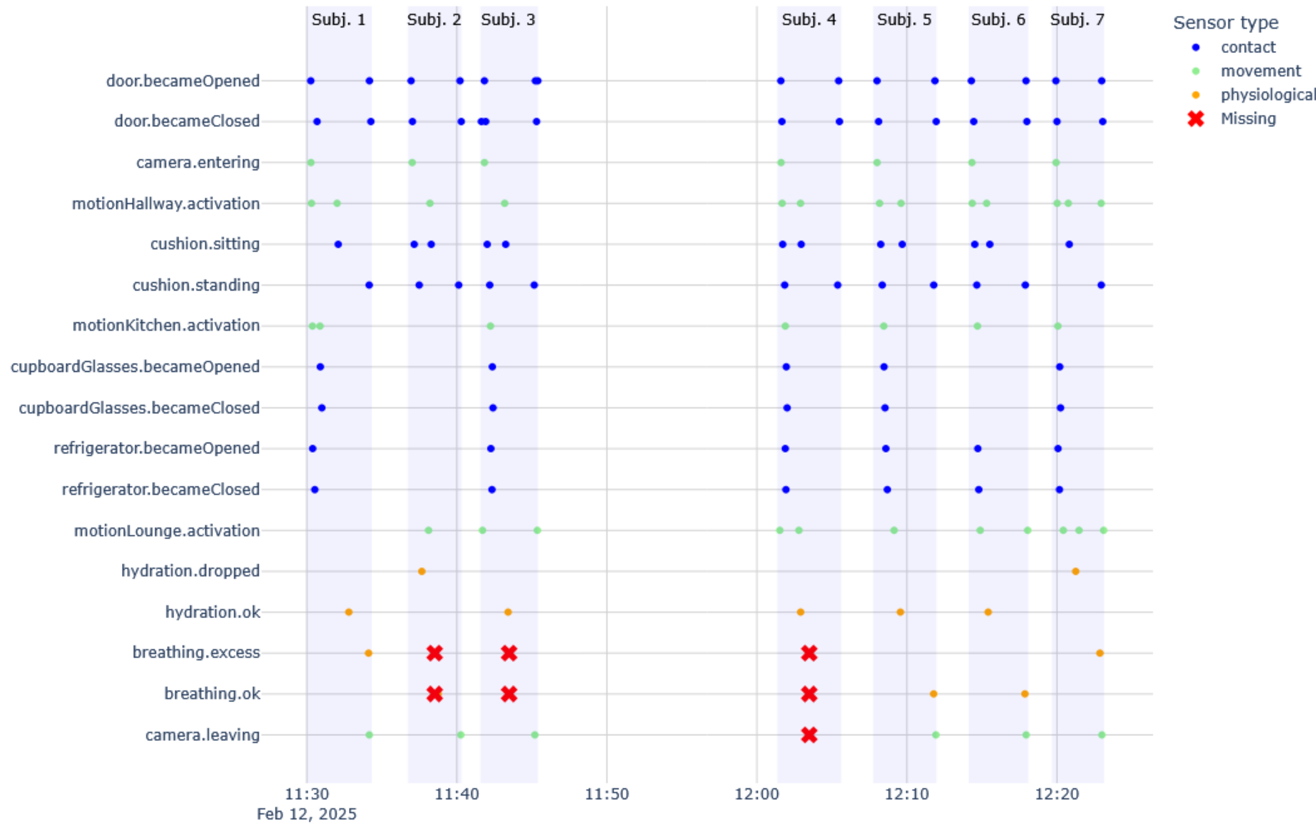


Figure 8. Sensor events during the experiments, ordered according to their expected occurrence, with blue shading indicating the experiment period for each subject, while red **X** markers denote missing data points.

Verification Using the Integrated Model

Property 1 is verified using a combined model of the camera and hydration sensor data, recall that:

- The hydration sensor records the subject's hydration state at a given time.
- The camera sensor detects when the subject leaves the environment.

The property describes the expected ordering of sensor conditions over time. A subject satisfies the property if hydration is normal shortly prior to exit. Although having a low or high hydration at home is not ideal, it does not constitute a violation of the property; the violation occurs only when the person exits the home and the hydration level is either low or high.

- The property is upheld for subjects 1, 3, 5 and 6. Hydration levels are normal shortly prior to the exit events captured by the camera.
- The property is upheld for subject 4. The hydration level for subject 4 is normal; however, the triggering condition corresponding to the subject exiting never occurs and the property therefore holds trivially. The technical explanation for the camera malfunction can be found in Appendix II: Individual Sensor Results.
- The property is violated for subjects 2 and 7. In both cases, a low hydration state is followed by the camera detecting the subject exiting. Low hydration is caused by the subjects not drinking any water as shown in Table 3.
  - Subject 2: The experiment runs from 11:36:44 to 11:40:19. Within this interval a low hydration level is detected at 11:38:10 and the subject leaving at 11:40:16.
  - Subject 7: The experiment runs from 12:19:40 to 12:23:08. Within this interval, a low hydration level is detected at 12:21:07 and the subject leaving at 12:23:00.

Individual results for the hydration and the camera sensors can be found in found in Tables 6 and 8 of Appendix II: Individual Sensor Results.

Note that the property allows for various events to occur between the detection of the subject's hydration level and their exit from the lab. For example, in Figure 8 we see that for subject 2, the low hydration (`hydration.dropped`) is followed by motion in the lounge (`motionLounge.activation`), motion in the hallway (`motionHallway.activation`) and then the subject exiting (`camera.leaving`). The explicit naming of the corresponding sensor events is provided here to illustrate the sequence used in the model. For the remaining properties, the discussion is kept at a higher level for brevity.

It should be noted that the level of hydration is only observed when the subject is seated on the cushion. Between measurements, changes in hydration cannot be detected unless the subject sits on the cushion again and a new measurement is taken. Therefore, the hydration level is treated as unchanged until a subsequent measurement is available.

Significance of Combining Camera and Hydration Sensors

By combining hydration and camera sensors, we collect data from different modalities, enabling a more comprehensive assessment of the subject before exit. A single-sensor analysis would either detect the hydration level without knowing whether the person had left (hydration sensor alone) or detect exit without knowing the hydration level (camera alone). Only by combining these modalities can the resulting analysis avoid the ambiguity inherent in single-sensor observations.

Hydration and Breathing Before Leaving Home (Property 2)

Property 2 requires that a person's hydration and breathing levels both have a normal state prior to leaving the home. This ensures that subjects do not exit while having abnormal hydration levels or abnormal breathing patterns.

Verification Using the Integrated Model

Property 2 is verified using a combined model of the hydration, camera and breathing sensors, the latter recording the subject's breathing state at a given time.

The property specifies what the subject's state of hydration and breathing should be when they exit. A subject satisfies the property only if, when exiting, both the hydration and breathing levels are normal.

- The property is upheld for subjects 5 and 6. Hydration and breathing levels are normal shortly prior to the exit events captured by the camera.
- The property is violated for subjects 1, 2 and 7. In subject 1, an excess breathing state was captured, while in 2 and 7, a low hydration state was captured (as mentioned in the results for Property 1).
  - Subject 1: The experiment runs from 11:29:57 to 11:34:20. Within this interval an excess breathing level is detected at 11:34:07 and the subject leaves the lab at 11:34:10.
- We do not have data to determine the outcome of the property for subjects 3 and 4. This is due to the host machine for the breathing sensor being inactive during these two experiments. This reflects the situation that may be encountered in practice when hardware problems may impact data collection.

Individual results for the hydration, breathing and the camera sensors can be found in Tables 6, 7 and 8 in the Appendix II: Individual Sensor Results.

Significance of Combining Hydration, Breathing, and Camera Sensors

Building on the previous property, the inclusion of an additional physiological modality introduces a breathing constraint at exit. By combining hydration, breathing and camera sensors, the resulting property requires both hydration and breathing to be normal, rather than relying on a single parameter (i.e. hydration). This property imposes a stricter condition than the previous one, providing greater confidence in the subject's overall physiological state.

Kitchen Safety: Refrigerator Door (Property 3)

Property 3 requires that the refrigerator door is open only when the subject is in the kitchen.

Verification Using the Integrated Model

Property 3 is verified using a combined model of the contact sensor on the refrigerator door and all sensors in the hallway and lounge.

- The contact sensor detects when the subject opens/closes the refrigerator.
- The combined hallway and lounge sensors detect any activity in their respective areas.

The property specifies how the refrigerator contact sensor relates with two distinct groups of sensors: all sensors in the hallway and all sensors in the lounge (recall room configuration in Section Model). This property makes use of multiple sensors to monitor any change outside the kitchen when the refrigerator is open.

A subject satisfies the property only if, after opening the refrigerator door, the refrigerator door is closed before any activity is detected in either the hallway or the lounge. No violations of Property 3 are observed in any of the experiments. Individual results for the refrigerator contact sensor can in found in Table 10 in Appendix II: Individual Sensor Results.

Significance of Combining Contact and Motion Sensors

The opening of the refrigerator door defines a period during which no sensor changes are expected in the hallway or the lounge until the door is closed, while activity within the kitchen, such as cupboard use or movement, may still occur. Integrating sensors across these areas allows changes in different rooms to be treated as a single condition that must not occur during this interval. This reduces the complexity that would arise from interpreting individual sensors in isolation and enables the property to be evaluated based on the absence of changes across multiple modalities.

Indoor Footwear Safety (Property 4)

Property 4 requires that the subjects take off their shoes in the hallway when entering the home.

Verification Using the Integrated Model

Property 4 is verified using a combined model of the contact, motion and cushion sensors; recall that:

- The contact sensor detects when the subject closes the door to the lab.
- The motion sensor detects when there is movement in the hallway.
- The pressure sensor detects when the subject sits on the cushion (on a stool next to the entrance).

The property is satisfied if after the door is closed, either: there is pressure on the cushion (indicating a subject sitting) or there is motion in the hallway, followed by pressure on the cushion.

- The property is upheld for subjects 2, 3, 4, 5, and 6.
- The property is violated for subjects 1 and 7. These violations occur because no sitting is detected on the pressure sensor after these subjects enter the room. During the experiments, subjects 1 and 7 avoid sitting down, as shown in Table 3.
  - Subject 1: The experiment runs from 11:29:57 to 11:34:20. Within this interval, the door is closed at 11:30:41 and 11:34:16. There is no sitting on the pressure cushion between these times.
  - Subject 7: The experiment runs from 12:19:40 to 12:23:08. Within this interval, the door is closed at 12:22:00 and 12:23:03. There is no sitting on the pressure cushion between these times.

Individual results for the contact, motion and pressure sensors can be found in found in Tables 9, 11 and 12 in the Appendix II: Individual Sensor Results.

Significance of Combining Contact, Motion and Cushion Sensors

By combining contact, motion and pressure sensors, we can identify key steps, expected to occur, when a person returns home. All three sensors capture the conditions associated with a subject entering the hallway and sitting on the cushion located in the hallway. The property allows some flexibility; specifically, it permits motion to be detected between the door closing and the subject sitting on the cushion.

Consistency of Entry Detection (Property 5)

Property 5 requires that whenever the camera detects a person entering the home, the event is preceded by the door opening and followed by the door closing, as recorded by the contact sensors. This ensures consistency between camera observations and door events. Note that the property is flexible to allow additional events, besides the entry detected by the camera, between the opening and closing of the door.

Verification Using the Integrated Model

Property 5 is verified using the combined model of camera and contact sensor events. An entry satisfies Property 5 if each camera-detected entry is preceded by a door opening and followed by a door closing event.

No violations of Property 5 were observed in any of the seven experiments. All entries were preceded by the door opening and followed by the door closing. In some instances, additional actions occurred between the camera detecting the subject entering and the door closing. For example, for subject 1, the refrigerator was opened and closed before the door was closed. This did not affect the outcome of the property, as it is designed to accommodate such nuances.

Individual results for the camera and contact sensors can be found in Tables 8 and 9 in the Appendix II: Individual Sensor Results.

Significance of Combining Camera and Contact Sensors

Property 5 allows us to cross-check camera-detected entries with door contact events, confirming the expected sequence (imposed by physical constraints) of the door opening, camera entry detection, and subsequent door closing. Since the camera and contact sensors are also used in previous properties, demonstrating their correct operation through Property 5 provides additional confidence in the outputs from the previous properties.

Discussion

The results presented in this study highlight the potential effectiveness and robustness of a multi-sensor integrated system for activity monitoring and behaviour verification within a controlled environment. We use model checking to formally verify properties concerning events of daily activities detected by the multi-sensor system. The observed behaviour is modelled as a sequence of events and is included as part of the model. We define properties that must hold in the model. Through the complementary use of diverse sensing modalities – including motion, camera, breathing, hydration, pressure, and contact sensors – our system captures a meaningful representation of human activity within a domestic environment.

One of the key strengths of our approach lies in the complementary capabilities offered by the various sensors. For instance, motion and camera sensors work together to track presence and movement direction with high confidence. The camera-based detection of entry and exit events provided confirmation of the subject's physical presence, while motion sensors helped confirm movement direction and space transitions, further enhancing confidence in state transitions within the model. The use of multiple sensor inputs enables the detection of signals that cannot be inferred from a single sensor alone, as reflected in the evaluated properties. Although some properties failed, these failures were caused by the subject's behaviour rather than by sensor malfunctions. Only a small number of sensor malfunctions were observed, occurring in the breathing and camera sensors (see Appendix II: Individual Sensor Results for details).

The hydration and motion sensors also demonstrate synergy. The hydration cushion provides physiological feedback about water intake, while the motion and contact sensors observe related behaviours – such as opening the fridge to drink water. Similarly, the pressure cushion sensor verifies whether subjects adhered to shoe-related hygiene tasks (e.g. sitting to remove or put on outdoor shoes), which, when combined with the camera and contact sensors, forms a richer behavioural pattern. This layering of information allows for the creation of more accurate models and improves fault tolerance by cross-validating sensor data.

The integration of Wi-Fi CSI-based breathing sensors introduces an unobtrusive method for the continuous monitoring of vital signs. However, we encountered missing data for Subjects 2 and 3 due to unexpected sensor downtime. This presents a significant challenge when verifying properties related to health status. To ensure continuity during verification and to avoid erroneous alarms due to gaps in sensor data, we adopted a conservative encoding strategy. When the breathing sensor is offline, there are no breathing events. This strategy allowed us to exclude false positives, and aligned with our data translation framework. Importantly, this issue reinforces the necessity of redundancy in smart home systems. The multi-sensor setup ensures that the absence or failure of a single sensor does not lead to system-level failure or misleading behavioural interpretations. For instance, even when breathing data are unavailable, hydration status and motion/camera data provided enough context to reason about aspects of general well-being and compliance with activity routines. Overall, the modelling approach demonstrated robust performance within the controlled experimental setting in verifying user behaviour against the specified properties. In particular:

1. The use of different subsets of sensors across the experiments highlights the modularity of the modelling approach, where combinations of sensors enable the specification and verification of properties that would neither be achievable nor reliable using a single sensing modality.

2. In terms of extensibility, the modular structure of the model allows additional sensors and properties to be incorporated with minimal changes. This suggests that the approach may be extensible beyond the current set of ADLs and sensing modalities as monitoring requirements change, although further evaluation in real-world settings is required.

3. The experiments demonstrate that property verification remains meaningful even when some sensor data are missing or unreliable (as with our breathing sensor). This is particularly relevant for future real-world deployment, where sensor malfunction/unreachability is possible. This suggests the potential suitability of the approach for long-term, in-home monitoring.

4. Observed behaviour within a specified time frame: The model checker identified violations when expected behaviours (e.g. shoe removal, water intake) did not occur. This level of granularity enhances interpretability and supports the potential use of this system in care or assisted living scenarios.

Taken together, the combination of symbolic model checking with a multi-sensor system demonstrates the capability of this approach for intelligent activity monitoring. The fusion of sensor inputs has the potential to improve accuracy and resilience to sensor faults within the evaluated setting.

Limitations

The current implementation of the system has some limitations. The study was conducted with a limited number of subjects in a controlled lab environment, which may not fully reflect the variability and complexity of real-home settings. Sensor placement and model property configurations were fixed although we believe that this does not constrain the model's adaptability to different domestic layouts. While the current properties capture a number of safety and functional constraints, more nuanced behaviour (e.g. gradual changes over time) are not yet addressed, so future work could explore richer temporal properties. Furthermore, the current symbolic model assumes single occupancy and a single sensor state transition at any given time. While this scoping aligns with the proof-of-concept, it restricts the application in broader real-world deployments. Concurrent activities, or the presence of other individuals or pets, would generate overlapping sensor data that the current model does not handle. Consequently, the system's immediate applicability is bound to strictly single-occupancy contexts.

In addition, several factors may influence the accuracy and consistency of some of the sensors. For instance, hydration sensor's accuracy and consistency can be affected by parameters that includes body composition, posture, clothing, sensor placement and environmental variability. In addition, inter-subject physiological differences may affect the observed S11 responses, potentially limiting the direct generalisability of fixed threshold values across different populations. Therefore, larger cohort studies are required to further evaluate the repeatability, robustness, and clinical reliability of the proposed sensing approach under real-world conditions. Furthermore, while the hydration and breathing sensors have been evaluated separately in previous publications, the present work focuses on assessing the feasibility of combining these sensing modalities with other sensors to support behavioural verification in a controlled environment.

Although we recognise these limitations, they do not diminish the value of the present work. Further testing will focus on recruiting volunteers from the ACRC's target age group (older adults) to further adapt the sensing setup. In the future, we plan to further evaluate acceptability and ethics of this multi-sensor system, as a follow-up to our existing work on the unobtrusiveness of the in-home sensors and qualitative work with key stakeholders, particularly older adults, to explore comfort, experienced obtrusiveness and perceived health benefits.

Conclusion

This study presented an integrated physiological and activities monitoring system that is designed to eventually support independent living. By integrating formal verification techniques with unobtrusive physiological sensors, behavioural and activity monitoring technologies embedded within everyday household environments, the system demonstrates the potential for reliable detection of behavioural deviations and health-related anomalies across multiple subjects within the controlled experimental setting. Furthermore, in cases where a sensor malfunctioned or data was missing, the readings from other sensors can be used to mitigate the issue.

Future work will include sensing modalities that capture additional parameters, such as heart rate and gait. Our longer-term goal is to field test our integrated platform in older peoples' homes, expanding on the work we have already done in the community[26]. This will allow us to evaluate complex, real-world scenarios, including unscripted activities, thereby improving interpretability and robustness for monitoring ADLs and potentially capturing behaviours of concern for older adults. This system serves as a showcase of the application of multidisciplinary collaboration and co-creation in integrating unobtrusive sensor technologies for activity and physiological modelling. Future work will also focus on validating some of the individual sensors against clinically established techniques, such as the hydration RF sensors. Further studies will also evaluate our system under more demanding conditions, such as multiple occupancy and over longer periods. Additional studies will also investigate longitudinal repeated measurements, subject-specific baseline calibration approaches and larger participant cohorts to improve the robustness, personalisation, and generalisability of the individual sensors and of the overall model.

Data Availability

The sensor data that support the findings of this study are archived by the University of Edinburgh as part of the Advanced Care Research Centre. Due to data access and governance constraints, these data are not publicly available. However, they may be made available from the authors upon reasonable request and subject to appropriate permissions.

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Author contributions statement

R.C., I.S., J.D.F. and J.H. contributed to the main manuscript and the design of the experiments. I.S., C.L., F.Y., A.A., U.A. and R.C. contributed to the operation of each sensor during the experiments. J.D.F., J.H., F.S. and R.C. contributed to the model section. R.C. developed the code for generating the models. All authors reviewed the manuscript.

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Additional information

Competing interests The authors declare that they have no competing interests.

Appendix I: Formalism and Property Specifications

Formalism

We are concerned with modelling behaviour over time. This makes Linear Temporal Logic (LTL)[44] appropriate for our work as it allows us to specify properties through the use of various temporal operators. LTL is a formalism used in formal verification to reason about temporal properties in a model. We use LTL extended with past-time operators[49], henceforth referred as past Linear Temporal Logic (pLTL).

We use pLTL to build formulas and then check whether all execution paths (sequences of states) of the model satisfy those formulas, where each state in the path is labelled with the atomic propositions that it satisfies. A formula consists of atomic propositions, logical operators and temporal operators. Formally, formulas are generated according to the following BNF grammar:

$$\phi, \psi ::= \quad p \mid \neg\phi \mid \phi \vee \psi \mid \phi \wedge \psi \mid \phi \rightarrow \psi \mid X\phi \mid Y\phi \mid F\phi \mid O\phi \mid G\phi \mid \phi\ U\ \psi \mid \phi\ R\ \psi$$

where ϕ and ψ are formulas.

An atomic proposition p is satisfied if the state at that index of the trace is labelled with it. The non-temporal logical operators $\neg$, $\vee$, $\wedge$ and $\rightarrow$ have the same meaning as in propositional logic[50]. Key temporal operators of pLTL are described in Table 5. This selection does not preclude the use of other operators; rather, it reflects those that are specifically chosen for the properties discussed in the paper, recognising that different properties may require different operators.

Using this formalism, we have specified a set of five properties. Each property makes use of one or more of the sensors previously described in the paper.

Table 5. Sample of temporal operators used in pLTL

Operator	Interpretation
Next (X)	In $X\phi$, ϕ is expected to hold at the immediate next time step.
Previous (Y)	In $Y\phi$, ϕ held at the time step immediately before the current one.
Eventually (F)	In $F\phi$, ϕ will hold at some point in the future, though not necessarily immediately.
Once (O)	In $O\phi$, ϕ held at some point in the past, at or before the current time step.
Globally (G)	In $G\phi$, ϕ holds at the current time and continues to hold at all future time steps.
Until (U)	In $\phi\ U\ \psi$, ϕ holds continuously up to a future point when ψ becomes true. At that point ψ must hold and ϕ must have held at every earlier step.
Release (R)	In $\phi\ R\ \psi$, ψ must hold at least until ϕ becomes true; if ϕ never becomes true, then ψ must continue to hold at all future time steps.

Property Specification

In our model, properties are specified in temporal logic and used to verify aspects of the system. We use these properties as a form of decision support: they allow us to reason about the state of the system and detect inconsistencies in the performance of ADLs. In what follows, we describe the properties used in our lab scenario. They are grouped under physiological safety, sensor operation, and general guidelines.

Physiological safety when leaving the home

When a person leaves the home, their hydration level must have been observed to be within the normal range prior to leaving.[51] This property is specified in LTL as follows:

Property 1

$$G\,(\texttt{camera.leaving} \rightarrow \; O\,(\texttt{hydration.ok} \wedge (\texttt{hydration.normal} \; U \; \texttt{camera.leaving}))) \tag{1}$$

The property in (1) specifies that it is always the case (G) that when a person leaves the home (`camera.leaving`), then at some point in the past (O) a normal level of hydration is detected (`hydration.ok`) and the hydration state triggered by that detection remained normal until the person left the home (`hydration.ok`$\rightarrow$ `hydration.normal`U`camera.leaving`). Note that the triggering of the *normal* hydration state is represented by `hydration.ok` (lasting one step). The state remaining *normal* is represented by (`hydration.normal`) and lasts until a new hydration sensor measurement is performed.

A variation of the above property is shown in (2). In this, the property specifies that *when a person leaves the home, both their hydration and breathing must have been observed to be within the normal range prior to leaving*[52]. The property states that in addition to hydration, a normal level of breathing is detected at some point in the past (O `breathing.ok`) and the breathing state triggered by that detection remained normal until the person left home (`breathing.ok`$\rightarrow$ `breathing.normal` U `camera.leaving`). Note that the triggering of the *normal* breathing state is represented by `breathing.ok` (lasting one step). The state remaining *normal* is represented by (`breathing.normal`) and lasts until a new hydration sensor measurement is performed.

Property 2

$$\begin{aligned} &G\,(\texttt{camera.leaving} \rightarrow \; O\,(\texttt{hydration.ok} \wedge \\ &\quad (\texttt{hydration.normal} \; U \; \texttt{camera.leaving})) \wedge O\,(\texttt{breathing.ok} \wedge \\ &\quad (\texttt{breathing.normal} \; U \; \texttt{camera.leaving}))) \end{aligned} \tag{2}$$

Safety Guidelines

The property in (3) derived from general guidelines proposed in our previous work[47]. The property states that *whenever the refrigerator door is open, the person must remain in the kitchen until the refrigerator door is closed*.

Property 3

$$\begin{aligned} &G\,(\texttt{refrigerator.becameOpened} \rightarrow \texttt{refrigerator.becameClosed} \; R \\ &\quad (\neg\, \texttt{hallway.change} \wedge \neg\, \texttt{lounge.change})) \end{aligned} \tag{3}$$

The property specifies that, it is always the case (G) that when the refrigerator door is opened (`refrigerator.becameOpened`) then closing the door (`refrigerator.becameClosed`) releases that changes can occur in the hallway (`hallway.change`) or in the lounge (`lounge.change`).

Another property, (4), states that *when a person enters the home they sit down on the stool, indicating they are taking off their shoes*. This is derived from general guidelines and found to be an important consideration in mitigating falls and risks of accidents in people's homes, as noted by Kim et al.[53] and Menz et al.[54]. As highlighted by Miyadera et al.[45], tasks like putting on footwear can challenge balance in older adults, and making the use of a chair or similar is a common precaution for enhancing safety and stability. We assume in our scenario that the subject uses a stool (equipped with a pressure cushion) when removing their footwear just after entering the home.

Property 4

$$\begin{aligned} &G\,(\texttt{door.becameClosed} \wedge Y\,(\neg\, O\,\texttt{door.becameClosed}) \rightarrow \\ &\quad X\,\texttt{cushion.sitting} \vee (X\,\texttt{motionH.detected} \wedge XX\,\texttt{cushion.sitting})) \end{aligned} \tag{4}$$

The property specifies that it is always the case (G) that when the door is closed for the first time after entering the home (`door.becameClosed` $\wedge$ Y ($\neg$ O `door.becameClosed`)) then in the next step, either someone is detected sitting on the cushion (X `cushion.sitting`) or motion is detected in the hallway, followed by someone sitting on the cushion in the step after that (X `motionH.detected` $\wedge$ XX `cushion.sitting`).

Sensor cross-checking

The property in (5) is used to cross-check the magnet and camera sensors when a person enters the home. This states that *the camera detecting an entry must be preceded by the door opening and eventually followed by the door being closed again.* The property specifies that is it always the case (G) that the event of the person entering the home captured by the camera (`camera.entering`) is preceded by the door being open in the previous step (Y `door.becameOpened`) and followed by the door being closed at some step after (F `door.becameClosed`).

Property 5

$$G\,(\texttt{cameraSensor.entering} \rightarrow Y\,\texttt{door.becameOpened} \wedge F\,\texttt{door.becameClosed}) \quad (5)$$

Appendix II: Individual Sensor Results

This section presents results for the individual sensors that figure in our system. The sensitivity, specificity and accuracy values reported here are based on data from scripted activities in a controlled lab environment. As such, they are not necessarily representative of a real-world environment.

Individual Sensor Results

Hydration Sensors

Figure 9 shows captured hydration data for each subject. These plots represent the average S11 for 4 RF sensors that were placed in the cushion. The average S11 data is shown for a wideband frequency range due to the sensor being an UWB antenna. In order to obtain the average S11 across the frequency range, this data was further processed to extract an average value that is then compared to the threshold values mentioned in Subsection Physiological Sensors that were obtained from our earlier study[29]. It can be seen that only two out of the seven subjects had an average S11 that was above the -22.5 dB threshold as specified in Subsection Physiological Sensors, which means that the subjects were "dehydrated". These two subjects (2 and 7) violated the hydration requirements (Properties 1 and 2) during the experiment. The hydration state is translated into the format shown in Table 6, where `hydration.ok` denotes the subject had normal hydration state (`hydration.normal`) and `hydration.dropped` denotes the subject had low hydration state (`hydration.low`). Note that none of the subjects exhibits high hydration.

The purpose of the hydration measurements in the present study differs from that of our previous work[29]. In the earlier study[29], the hydration sensor was developed and experimentally evaluated under controlled hydration protocols to establish the relationship between changes in body hydration and the measured S11 response, leading to the empirical threshold values used in this work. In contrast, the present study does not seek to evaluate the hydration sensing technology itself. Rather, it employs the previously established sensing methodology and thresholds as inputs to a multimodal monitoring framework, where hydration events are combined with behavioural sensor data and analysed using formal verification.

Nevertheless, within the current proof-of-concept dataset, the previously established threshold correctly classified all seven participants with respect to the hydration states observed during the experiments. Using the -22.5 dB threshold as the classification criterion, the system identified dehydration cases with an observed sensitivity of 100% and specificity of 100% within this limited experimental cohort, corresponding to zero false positives and zero false negatives. Consequently, the precision and negative predictive value were also 100% for the recorded dataset. However, these performance metrics should be interpreted cautiously due to the small sample size and the absence of validation against clinically established hydration assessment methods. Larger-scale studies incorporating diverse participants and repeated longitudinal measurements are required to more rigorously evaluate the robustness, repeatability, and generalisability of the proposed RF-based hydration sensing approach.

Table 6. Conversion of Captured Hydration States to Model Properties.

Subject	Experiment Time	Avg. Hydration Sensor Reading (dB)	Hydration Event
Subj. 1	11:31:06	-36.7	`hydration.ok`
Subj. 2	11:38:10	-19.6	`hydration.dropped`
Subj. 3	11:42:53	-39.5	`hydration.ok`
Subj. 4	12:03:20	-50.3	`hydration.ok`
Subj. 5	12:09:37	-68.8	`hydration.ok`
Subj. 6	12:15:58	-37.4	`hydration.ok`
Subj. 7	12:21:07	-18.2	`hydration.dropped`

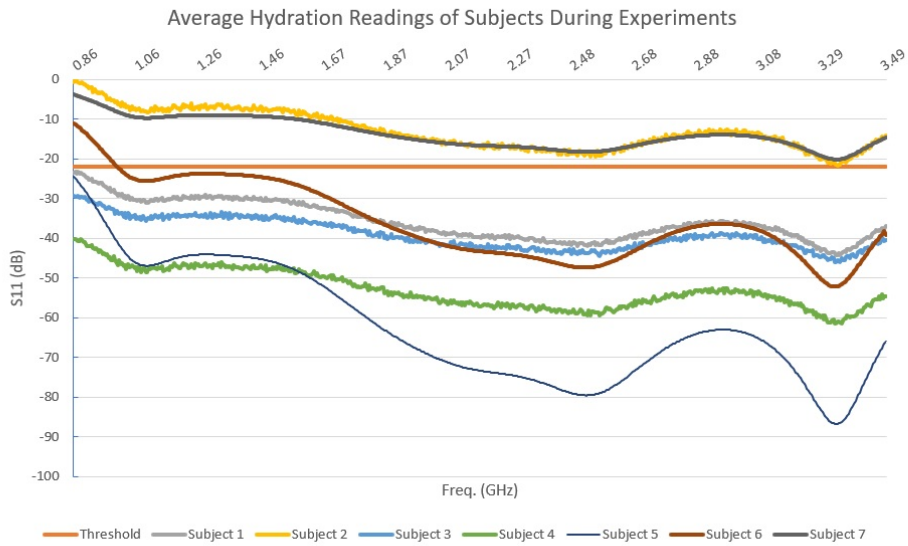


Figure 9. Captured hydration measurements during experiments.

Breathing Sensors

After acquiring the raw CSI signal, the data is processed to extract the micro-movement variations associated with breathing. Table 7 shows the results for each subject and their translations to states in the model. We note that for Subjects 2 through 4, a sensor failure occurred during the experiments, with the receiver station powering off without notice. This further emphasises the need for a multi-sensory smart-home approach like ours. For Subject 2, the 30 seconds of data recorded before sensor failure is used as the sensor state. The outputs are subsequently mapped to `breathing.ok` or `breathing.excess` based on the values obtained from the average wavelet energy graphs, calculated from the Morelet scalograms as shown in Figure 10a and 10b respectively.

The breathing segment for the property for Subject 6, used a metronome to guide breathing at 12 BPM. The BPM values used in the experiments were selected based on typical breathing rates. Therefore, the reported results may not generalise to substantially slower or faster breathing patterns, such as those observed during meditation. The peak of the average wavelet energy, representing the subject's breathing rate, is captured at 12.5 BPM. This value is obtained from a standard conversion from the peak of the average wavelet graph (see Figure 10a). Similarly, the breathing segment for subject 7 used a metronome to guide the breathing at 20 BPM. The peak of the average wavelet energy, representing the subject's breathing rate, is captured at 19.5 BPM. Similarly, this value is also obtained from a standard conversion from the peak of the average wavelet graph[55] (see Figure 10b).

The validity of the Wi-Fi CSI respiration sensor has been established in our previous work through comparison with a ground-truth respiration belt under both controlled and uncontrolled conditions, achieving measurement accuracies of 96.90% and 89.25%, respectively[56,57]. The present study utilises the previously validated respiration sensor as one component of the integrated monitoring framework, where respiration measurements are translated for behavioural verification.

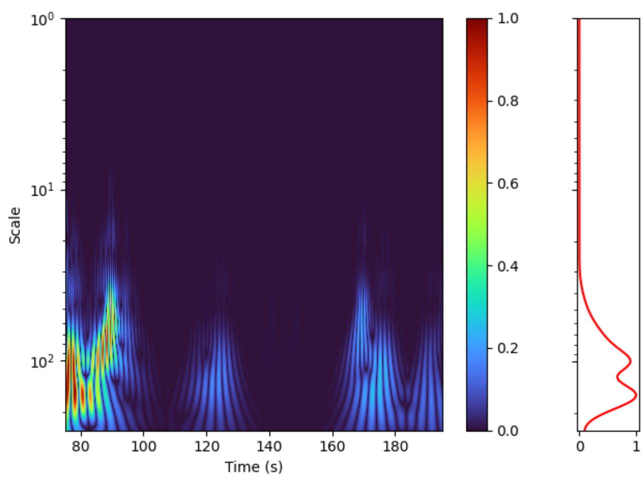
Within the current proof-of-concept experiments, breathing measurements were successfully acquired for subjects 1, 5, 6, and 7. For these subjects, the respiration rates estimated by the Wi-Fi CSI sensor corresponded to the metronome-guided breathing protocol and were translated into events (e.g. `breathing.ok`) used in the model. Subjects 2, 3, and 4 experienced incomplete data acquisition due to an unexpected receiver shutdown caused by PC power-management settings. These recordings were therefore excluded from the breathing analysis. Building on the sensor validation reported in previous studies[56,57], the present study shows that the previously validated respiration sensor can be integrated within the monitoring framework and provide reliable symbolic inputs for model checking when data acquisition is completed successfully.

Camera Sensor

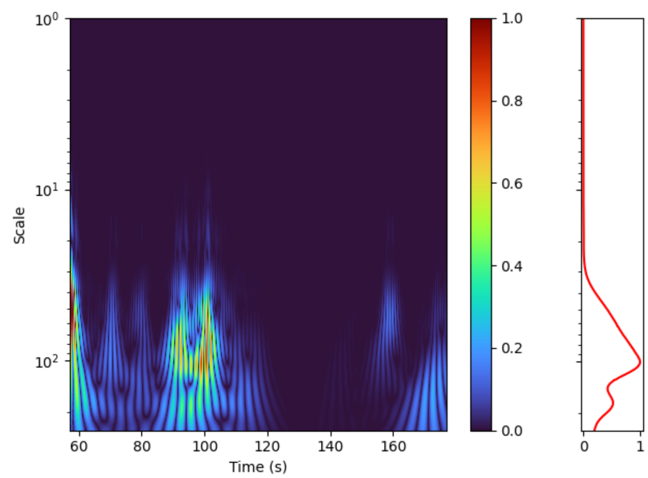
To enhance the accuracy of human presence detection, a combination of a lightweight 2D pose estimation method[58] and YOLOv5 object detection[59] is employed. When both methods independently detect a human with a confidence score exceeding 50%, the 2D human pose coordinates and bounding box are recorded along with a timestamp. The centroid of the detected human region is then extracted to infer the direction of movement. Specifically, the system determines whether the individual is moving toward the door (indicating exit) or moving away from the door (indicating entry). These activities are recorded in text

Table 7. Conversion of Captured Respiratory Rates to Model Properties.

Subject	Time	Extracted RR Value	Respiration Event
Subj. 1	11:34:07	16.39 BPM	`breathing.excess`
Subj. 2	11:38:45	13.17 BPM	`breathing.ok`
Subj. 3	11:45:07	Sensor OFF	—
Subj. 4	12:05:22	Sensor OFF	—
Subj. 5	12:11:47	11.27 BPM	`breathing.ok`
Subj. 6	12:17:52	12.5 BPM	`breathing.ok`
Subj. 7	12:22:52	19.5 BPM	`breathing.excess`



(a) Continuous Wavelet Transform Morelet scalogram for subject 6; peak of the average wavelet energy is at 12.5 BPM



(b) Continuous Wavelet Transform Morelet scalogram for subject 7; peak of the average wavelet energy is at 19.5 BPM

Figure 10. Signal Processing and Extraction output example of Activate and Deactivate states. The vertical axis corresponds to the scale of the wavelet in the spectrogram (equivalent to frequency in wavelet analysis), while the colours denote the normalised energy information carried by the signal at a specific time (x-axis) and scale (frequency).

Table 8. Conversion of Camera-Captured Door Events to Model Properties.

Subject	Time	Camera Detection	Event
Subj. 1	11:30:16	Entry	`camera.entering`
Subj. 1	11:34:10	Exit	`camera.leaving`
Subj. 2	11:37:01	Entry	`camera.entering`
Subj. 2	11:40:16	Exit	`camera.leaving`
Subj. 3	11:41:50	Entry	`camera.entering`
Subj. 3	11:45:12	Exit	`camera.leaving`
Subj. 4	12:01:36	Entry	`camera.entering`
Subj. 5	12:08:00	Entry	`camera.entering`
Subj. 5	12:11:56	Exit	`camera.leaving`
Subj. 6	12:14:20	Entry	`camera.entering`
Subj. 6	12:17:57	Exit	`camera.leaving`
Subj. 7	12:19:56	Entry	`camera.entering`
Subj. 7	12:23:00	Exit	`camera.leaving`

format, capturing the exact timestamps of appearance and disappearance in order to calculate the duration of each activity. For example, an entry activity is logged as "Person entered the door at DD:HH:MM:SS:MS, duration: X seconds,". For 7 subjects, 13 out of 14 total room entry and exit activities were correctly detected (Accuracy: 92.86%). The average entry duration is 1.0 seconds, and the average exit duration is 1.3 seconds. One outlier over 190 seconds occurred because subject 4 was chatting while standing halfway through the doorway (remaining in the camera's view the entire time). The door events captured by the camera are shown in Table 8. In the table, `camera.entering` refers to the subject entering through the door whereas `camera.leaving` refers to the subject exiting through the main door.

Contact and Motion Sensors

Data were collected for one hour. Both motion and contact sensors operate on an event-driven basis and are connected to a Phoscone II BEE gateway. As specified in section Contact and Motion Sensors, we use Home Assistant to orchestrate data acquisition from the motion and contact sensors and store our data using InfluxDB.

Tables 9 and 10 show the timestamps for the events captured by the door and refrigerator contact sensors during the experiments. Table 11 shows the timestamps for motion detection in the hallway. Based on our observations, no obvious errors (false positives, false negatives, or incorrect timestamps) were detected in the recorded events.

Pressure Sensor

The pressure sensor uses a program that only captures the duration a subject sits on the stool (i.e. the period over which the integrated pressure sensor is activated). This can be seen in Table 12. Although the pressure sensor has the capability to detect pressure changes caused by the subject sitting on the stool to analyse motion amplitude, in this model the program has been simplified to reduce the amount of unnecessary data processing. The sensor samples pressure at 2-second intervals during the experiments; therefore, the maximum uncertainty in the measured activation time is 2 seconds. In Table 12, the results show that five out of seven subjects sat on the chair to remove their shoes upon entering the room. For the other two subjects (i.e. Subjects 1 and 7), the pressure sensor was never activated after they entered the room; therefore, this suggests that the two subjects did not sit on the stool and remove their shoes. This result correlates correctly with the actions in Table 3, where Subjects 1 and 7 do not perform the action "Sit on cushion and take off shoes" during the experiments. The cushion sensor recognises whether a subject is seated by measuring the total pressure on the pressure sensor array, recording the movement amplitude based on pressure variations. In this experiment, five subjects sat to remove their shoes upon entry, and all seven subjects sat to check their breathing before exiting. The cushion sensor successfully detected all sitting and standing events along with their respective timings; thus, the system achieved 100% accuracy for activity detection.

Table 9. Contact door

Subject	Time	Event
Subj. 1	11:30:15	door.becameOpened
Subj. 1	11:30:41	door.becameClosed
Subj. 1	11:34:10	door.becameOpened
Subj. 1	11:34:16	door.becameClosed
Subj. 2	11:36:56	door.becameOpened
Subj. 2	11:37:02	door.becameClosed
Subj. 2	11:40:12	door.becameOpened
Subj. 2	11:40:17	door.becameClosed
Subj. 3	11:40:21	door.becameOpened
Subj. 3	11:41:37	door.becameClosed
Subj. 3	11:41:50	door.becameOpened
Subj. 3	11:41:55	door.becameClosed
Subj. 3	11:45:14	door.becameOpened
Subj. 3	11:45:18	door.becameClosed
Subj. 3	11:45:23	door.becameOpened
Subj. 4	12:01:35	door.becameOpened
Subj. 4	12:01:40	door.becameClosed
Subj. 4	12:05:27	door.becameOpened
Subj. 4	12:05:30	door.becameClosed
Subj. 5	12:08:00	door.becameOpened
Subj. 5	12:08:06	door.becameClosed
Subj. 5	12:11:52	door.becameOpened
Subj. 5	12:11:57	door.becameClosed
Subj. 6	12:14:17	door.becameOpened
Subj. 6	12:14:27	door.becameClosed
Subj. 6	12:17:56	door.becameOpened
Subj. 6	12:17:59	door.becameClosed
Subj. 7	12:19:55	door.becameOpened
Subj. 7	12:22:00	door.becameClosed
Subj. 7	12:22:59	door.becameOpened
Subj. 7	12:23:03	door.becameClosed

Table 10. Contact refrigerator

Subject	Time	Event
Subj. 1	11:30:23	refrigerator.becameOpened
Subj. 1	11:30:32	refrigerator.becameClosed
Subj. 3	11:42:16	refrigerator.becameOpened
Subj. 3	11:42:20	refrigerator.becameClosed
Subj. 4	12:01:53	refrigerator.becameOpened
Subj. 4	12:01:56	refrigerator.becameClosed
Subj. 5	12:08:35	refrigerator.becameOpened
Subj. 5	12:08:41	refrigerator.becameClosed
Subj. 6	12:14:43	refrigerator.becameOpened
Subj. 6	12:14:47	refrigerator.becameClosed
Subj. 7	12:20:04	refrigerator.becameOpened
Subj. 7	12:20:10	refrigerator.becameClosed

Table 11. Motion in hallway

Subject	Time	Event
Subj. 1	11:30:18	motionH.detected
Subj. 1	11:32:01	motionH.detected
Subj. 2	11:38:12	motionH.detected
Subj. 3	11:43:11	motionH.detected
Subj. 4	12:01:40	motionH.detected
Subj. 4	12:02:54	motionH.detected
Subj. 5	12:08:10	motionH.detected
Subj. 5	12:09:36	motionH.detected
Subj. 6	12:14:21	motionH.detected
Subj. 6	12:15:18	motionH.detected
Subj. 7	12:20:01	motionH.detected
Subj. 7	12:20:45	motionH.detected
Subj. 7	12:22:57	motionH.detected

Table 12. Conversion of Sitting Events in the hallway Area to Model Properties.

Subject	Pressure Sensor Activation Time Duration	`cushion.sitting`	`cushion.standing`
Subj. 1	No Recorded Time	/	/
Subj. 2	11:37:09 - 11:37:29	11:37:09	11:37:29
Subj. 3	11:42:01 - 11:42:11	11:42:01	11:42:11
Subj. 4	12:01:43 - 12:01:51	12:01:43	12:01:51
Subj. 5	12:08:15 - 12:08:21	12:08:15	12:08:21
Subj. 6	12:14:31 - 12:14:39	12:14:31	12:14:39
Subj. 7	No Recorded Time	/	/