Older Generation: Self-Powered IoTs, Home-Life and "Ageing Well"

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Abstract

Internet of Things (IoT) technology is found in many homes. These systems enable tasks to be done more effectively or efficiently – e.g., securing property, monitoring and adjusting resources, tracking behaviours for well-being, and so on. The system presented here was designed with older adults; the vast majority of home IoT systems marketed to this age group are not growth-oriented but rather decline-focused, monitoring and signalling well-being issues. In contrast to both "mainstream" and "older adult" IoT frameworks, then, we present a toolkit designed *only* to platform reflections, conversations and insights by occupants and visitors in regards to diverse user-defined meaningful home activities: hobbies, socialisation, fun, relaxation, and so on. Furthermore, mindful of the climate crisis and the battery recharge or replacement requirements in conventional IoT systems, the toolkit is predominantly self-powered. We detail the design process and home deployments, highlighting the value of alternative data presentations from the simplest to LLM-enabled.

NordiCHI 2024, October 13–16, 2024, Uppsala, Sweden

ACM ISBN 979-8-4007-0966-1/24/10
https://doi.org/10.1145/3679318.3685410

CCS Concepts

• **Human-centered computing** → *Participatory design*; *Interaction techniques*; *Field studies*; • **Hardware** → *Sensor applications and deployments.*

Keywords

Older adults, Internet of Things, self-powered interactions, co-design, deployment

ACM Reference Format:
Gavin Bailey, Krishna Seunarine, Carlos Baptista De Lima, Matt Carnie, Zaid Haymoor, Martin Hyde, Ben H Jones, Matt Jones, Jennifer Pearson, Thomas Reitmaier, Simon Robinson, Deepak Ranjan Sahoo, and Aelwyn Williams. 2024. Older Generation: Self-Powered IoTs, Home-Life and "Ageing Well". In *Nordic Conference on Human-Computer Interaction (NordiCHI 2024), October 13–16, 2024, Uppsala, Sweden.* ACM, New York, NY, USA, 14 pages. https://doi.org/10.1145/3679318.3685410

1 Introduction

> *Beep.* There's someone in the kitchen. *Beep.* The thermostat HALLWAY has been turned down. *Beep.* Sounds like a dog barking in the living room . . .

Every day, one of the author team[1] receives multiple notifications on their smart-watch from an array of IoT devices in their home;

[1]Positionality: two of the paper's authors identify as older adults.

a sample is shown in the box above. While each of these devices (cameras, thermostats, lighting controls, etc.) were bought to do a particular thing (like checking on the pets or securing their home) this author's long-term experience of such devices has uncovered uses presumably not designed-in by the manufacturer. While at home and away, this author feels connected to the home-life and has found themselves often reflecting on what the notifications might mean: *"Dogs barking – that will be the mail delivery; I wonder who has ordered something?... Thermostat's down; my partner must be back as they don't like it warm ... "*. In contrast to the *incidental* use of task-focused IoT output, in this work we engaged in a design process that led to a toolkit that is *purposefully* designed specifically for such reflections.

One group of users that has had a great deal of attention in terms of IoT support are older adults.[2] Despite the decade old call-to-arms by Rogers and Marsden [32] to move beyond frailty and declinist drivers in developing such systems for older adults, this framing remains dominant [40]. As more and more older adults will live "well" in their homes[3] there is a significant need to explore alternative IoT systems for this population.

We took up Rogers and Marsden's challenge in this work by engaging with older adults who are committed to "ageing well" for themselves and others. The purpose of our studies was to surface these groups' views of existing IoT approaches and to work with them to consider alternatives. We learned that while they could imagine why *other* older people might need the sorts of monitoring for health and well-being commonly provided by such systems, *they* saw such interventions as patronising invasions of privacy for people like them. Rather than seeing their lives as fragile, limited, and in decline—to be protected—they spoke of activities at home that led to growth, challenge and creativity – hobbies, socialising, laughter, and learning. The toolkit we present in this paper is designed to surface these forms of home life and to present them to platform reflection and connection, things that can be especially valuable to older age-groups. In addition, prompted by participants' concerns about inequalities, the environment and cost-of-living pressures [34], the toolkit is predominantly self-powered.

In contrast to prior work, our *primary* contribution is a novel IoT framing and toolkit that: amplifies older adult agency, enabling them to choose how to instrument objects and/or locations in their homes related to the life of the home as they perceive it; and, provides presentations to scaffold personal interpretations. In addition, a *secondary* contribution is to show how the sensing for such a system can be achieved through novel self-powering configurations.

2 Background

Our initial motivation was a desire to engage older adults in ways that recognised their agency and creativity for future technology [12] with an especial emphasis on IoT, a class of technology that has received much attention in regards to older adults [21] with much of it framing such users as "patients" (e.g., [23, 40]). In particular, a significant use-case for IoT home sensing is to provide health and well-being monitoring and interventions (e.g., [3, 11]). Typically, systems track deviations in behaviours known to flag potential decline (e.g., failure to carry out routine hygiene tasks), alerting a care-giver or the older adult themselves. While the majority of the tracked behaviours are practical in nature, Tewell et al. show how "meaningful" activities (such as those providing emotional enjoyment) might similarly be automatically monitored [38].

While ageist and declinist models of getting older still dominate design approaches [9], Ambe et al. [2], through IoT co-design workshops, argue the value in exploring frameworks that, *"... support more personal and creative interactions and aesthetics."* Ambe et al. also present older adult design fiction results to encourage a move beyond the "watchman" framing of IoT [1], and we address these suggestions in our work. Slow technology is a design philosophy that promotes such reflective engagements [29], and we consider ways of integrating and presenting the instant daily fast-firing of multiple independent home IoT sensors in ways that enable longitudinal reflections.

Prior work has demonstrated human and machine learning success in reasoning about and inferring behaviours from IoT home sensor data (e.g., [15, 16, 28]). Kurze et al. further show that people can make assessments of what might be happening in a home from the outputs of very simple sensors (e.g., light, motion, temperature), making the case that privacy and surveillance concerns associated with more advanced devices, such as cameras and microphones, should not be dismissed in regards to the simpler, "dumb" devices. Unlike [20], though, the system we present was designed with older adults with a primary goal of reflection on positive, meaningful home activities rather than this happening as a side-effect of sensor data or as research tool to surface practical and ethical concerns. Our work emphasises the smartness of users in interpreting "dumb" sensor outputs in contrast to work that foregrounds the "smartness" technology as a partner to older adults (e.g., [31]). Having said this, earlier work has shown the value of using digital innovation to enable creative ways of surfacing IoT sensor data to further scaffold user interpretations, including story narratives, an approach we adopt via a Large Language Model (LLM) [10].

One reasonable criticism of any novel IoT system is the additional demands it places on energy requirements in a world that is already wounded by non-sustainable behaviours. Such critical voices might be louder still for toolkits such as ours that do not appear to do "essential" tasks like keeping occupants safe. Furthermore, if toolkits such as ours adopted the standard approach of using replaceable batteries in deployed sensors, older adults could be negatively impacted. Devices might be placed in hard-to-access areas, which could be potentially dangerous to those with mobility concerns or at risk of falling. Age-related cognitive impairments could mean that the user faces difficulties replacing batteries [30], and often the battery changing itself requires a level of manual dexterity that can decline with age [7]. In creating the toolkit, then, we have limited ourselves to creating components that are powered by energy harvesting. We draw then on technical work that has considered low- and self-powered interfaces and interactions that maximise energy-harvesting from ambient light [19, 22, 24, 25, 27], movement [14, 39, 41], other sources [6, 26, 44], and hybrid harvesting means [18, 36, 37].

[2]The Health and Retirement Survey in the USA, the Survey of Health, Ageing and Retirement in Europe, and theEnglish longitudinal study of ageing all start data collection at age 50 – see: https://health.gov/healthypeople/objectives-and-data/data-sources-and-methods/data-sources/health-and-retirement-study-hrs (USA), https://share-eric.eu/ (Europe) and https://www.elsa-project.ac.uk/ (UK).
[3]https://www.ons.gov.uk/ageing/profileoftheolderpopulation/2023-04-03

The possibility of wide-area sensing using self-powered sensors has been demonstrated in prior work [4, 42–44]. OptoSense [43], solely relies on ambient light energy harvesting and demonstrates several applications (e.g., medication reminders, open door sensing, liquid sensing and indoor traffic sensing). The issue with solely relying on ambient light energy harvesting is the lack of sufficient illuminance in residential deployment locations. The authors of OptoSense used the IES Handbook [17] to create their recommended lighting conditions using incandescent lighting; however, the illuminance values that they chose begin at 250 lux (which represents the recommended lighting for task areas in offices and classes). These values are considerably higher than those recommended for residential lighting, where IES recommends illuminances of between 5 and 10 ft-c (approx 50–100 lux) in hallways, and 10 to 20 ft-c (approx 100–200 lux) in living rooms. National lighting standards[4] state that it is acceptable to drop lighting levels down to one third of the task area in the immediate areas surrounding it and that background areas (i.e., walls and ceilings – areas where we would want to attach PV-IoT devices) can be even lower, even all the way down to 50 lux. So, while PV powered sensors may work well in laboratory test environments, they fail to perform in actual residential deployments due to insufficient ambient light energy that is available for harvesting. Note that many dwellings were built long before modern building regulations and lighting standards, so the situation is worse and actual ambient light availability is much lower than anything indicated by any modern residential lighting norms [35].

Unlike OptoSense, Sozu [44] investigates the use of multiple sources of energy-harvesting (e.g., motion, vibration, light, electromagnetic radiation and water). The Sozu system uses radio frequencies as a method of identifying each sensor, and due to each of these requiring a unique radio frequency, *"supports up to 96 tags"* (sensors). Our system uses connectionless Bluetooth Low Energy (BLE) beacons, and as a result this limitation does not apply. We built on these works by incorporating multiple forms of energy harvesting and interaction sensing, whilst presenting these interactions to the user in meaningful and timely interpretations.

3 Designing the system

To develop the system we convened two day-long design sessions. The first considered older adults' views of home-based IoT systems to uncover issues that any design might address. These factors drove the form of a concept design that was refined by the older adults in the second workshop, two months later. Both sessions were convened in a design suite purpose-built to enable older adults to actively shape future technologies. The facility combines conventional workshop spaces with simulated spaces as shown in Fig. 1.

The Swansea University Faculty of Science and Engineering Ethical Review Board assessed and endorsed all of the workshops and studies presented in this paper: this process considers the detailed plans for each activity, with Board members drawn from across the disciplines in the Faculty.

[4]A summary of various standards and common practices is provided at https://ledil.com/news_all/articles-and-whitepapers/office-lighting-standards/

3.1 Workshop I: Exploring views on home-based IoT systems

For the first workshop, we recruited 14 participants (9F, 5M; ages 52–76, mean 69.4, s.d. 6.6 and with a mix of socio-economic backgrounds) through the group Swansea Ageing Well whose members are dedicated to "ageing well". This organisation is one of many seen in the UK dedicated to helping members build meaning, connection and well-being in old age. Each participant was given a shopping voucher as a token of our appreciation. In designing the workshops and analysis methods we were mindful of those used in prior older adult studies (e.g., [21]).

Participants were split into three groups randomly, with group sizes of 5, 5, 4. During the day, groups took part in six activities: i) a discussion of their early memories of non-digital home technologies; ii) discussion of their early memories of digital home technologies; iii) a day-in-the-life activity where participants walked us through the physical and digital devices/objects they used at morning, noon and night; iv) discussion of current standard IoT home devices (e.g., smart lightbulbs); v) using three simulated environments in our older adult innovation lab—kitchen, living area and garden—a bodystorming [33] activity on what digital services might be useful in that context; and vi) discussion of IoTs targeted at older people. Activities (i) and (ii) were used as "ice-breakers," allowing participants to easily contribute based on their past experiences. Our range of approaches drew on established participatory design practices for older adults [13]. For every activity, a facilitator and note-taker were assigned to each group. The facilitator led each session, ensuring the groups kept within the discussion points and noting key points on a flip-chart, while the note-taker was tasked with creating a detailed record of what was said by participants (see Fig. 2).

After the workshop, we used an inductive approach to thematic analysis with the steps laid out by Braun and Clarke [5] followed iteratively. The first author familiarised themselves with the data and generated the initial codes. Following this, both the first and second authors further refined the codes to surface themes. These results were presented to the wider project team, who reviewed the themes and helped to refine them into their final form.

3.1.1 Findings.

Diverse and full home-lives. Contrary to the declinist narrative in many research articles, our participants evidenced a very wide range of interests and activities that fill their lives at home and when out. They demonstrated a "growth" mindset – one that we celebrate in our framing of this paper. These discussions provided a useful reminder that older adults should not be catered for in a technologically-homogeneous way, as is often the case for this demographic, and especially so for IoT systems.

Monitoring. Home monitoring was seen as primarily an imposition on their home life by others (family, care-givers or professionals). As our participants were living independently they saw value in these systems for people they knew who were frail or needed support, but no use in their own lives.

Privacy in regards to smart technologies was a key issue. Participants had heard in the media that smart speakers are always listening and were very concerned about this. Similarly, there was shared concern over the examples of home monitoring that required

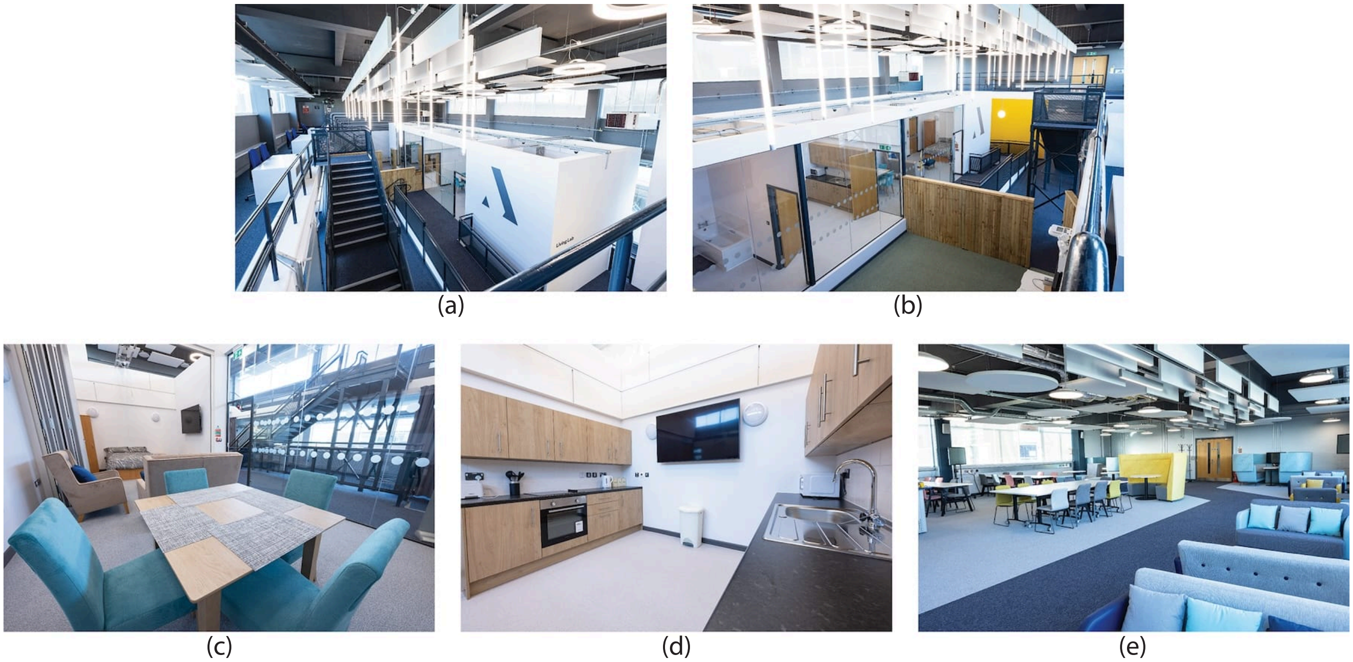

Figure 1: The living lab space (a, b) used in the two participatory design sessions. The space includes workshop areas (e) and simulated environments (living/bedroom (c), kitchen (d), garden (partly shown in (b))).

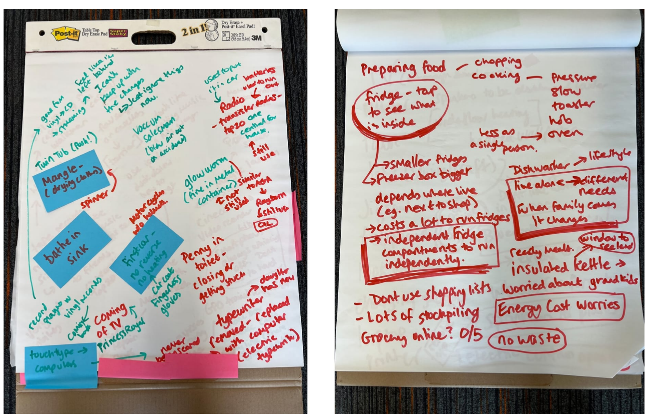

Figure 2: Example artefacts from design activities. Left: points from activity (i); Right: activity (v).

camera installations (e.g., *"I would not want my daughter to be able to watch me at anytime – you don't know what I could be up to!"*).

Resource requirements. Our participants were very concerned with the amount of energy they were using, both in terms of the environmental impact and the cost of living. They felt that the initial cost to buy home devices was too high and the need to be plugged in was not ideal.

3.2 Concept design

After the first workshop and over a period of two months, the design team created a home IoT concept shaped by that workshop's findings. That is, the concept aimed to afford a form of *monitoring* that might be of interest to older adults who are "ageing well," surfacing their *rich home lives* in a way that prioritises *privacy* and *reduces resource costs.*

The features of the proposed system were:

(1) A multiplicity of simple sensors (cf. [20]) that could be attached to objects and locations throughout a home at low cost (see Fig. 3 (top)).
(2) Objects and locations in the home would have significance with regards to meaningful experiences and activities in the home (e.g., "fun", "socialising," "hobbies").
(3) Sensors would generate simple "pings" when the objects or location in the home were active.
(4) These "pings" would be presented on simple physical display objects placed in living areas in the home to surface the life of the home (see Fig. 3 (bottom)).
(5) The sensors and displays would as far as possible be self-powered.
(6) The transmission of the sensor data and the processing would be privacy preserving using low-powered wireless transmission and non-internet-connected computing elements.

3.3 Workshop II: Refining the design concept

We recruited 16 participants (12F, 4M; age 59–84, mean 71.2, SD 6.3, mix of socio-economic backgrounds) through the same Swansea Ageing Well group. Six of the participants had taken part in Workshop I; the other ten were recruited to provide fresh perspectives. Each participant was given a shopping voucher.

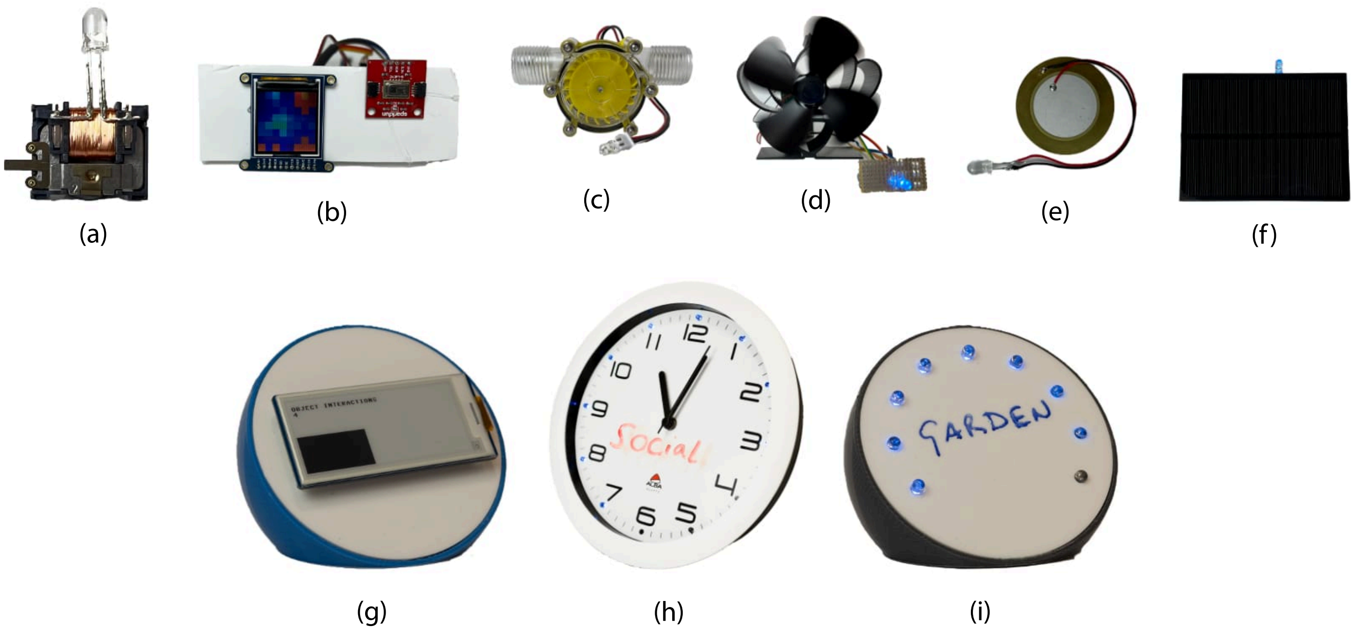

Figure 3: Top: Six low-cost energy-harvesters-cum-sensors that were demonstrated in Workshop II: (a) a kinetic-energy switch that could be attached to doors, drawers, etc.; (b) a photovoltaic (PV) powered low-resolution thermal imaging camera to detect movement; (c) a hydroelectric sensor for taps, hoses, etc.; (d) a thermoelectric sensor for placing on, for example, stoves; (e) piezo-electric sensors embedded in floors or steps; and, (f) PV surface sensors that could be embedded in objects that are intermittently exposed to light (e.g., bookmarks, coasters, etc.). Bottom: Three forms of simple display that were used in Workshop II to illustrate potential outputs from the home IoT system: (g) coffee-table pods with an E ink display showing a graphical representation of today's activity; (h) a conventional kitchen clock with light outputs; and, (i) pods with a light display, again, to signify the quantity of "pings" sent for a meaningful activity/experience.

During the day-long workshop, participants took part in three activities to progressively introduce and elaborate the concept design. For the first two activities, participants were split into three groups of a similar size (5, 5, 6) with a similar ratio of M/F and previous/new attendees in each group. For the last activity, two larger groups (8, 8) were formed. For each activity, the discussion was facilitated by a member of the research team using a flip-chart to capture key points as the discussions progressed, while another acted as a detailed note-taker.

Activity 1 – The life of the home. Participants were asked about positive and important activities they regularly did at home such as socialising, hobbies, fun and creativity. For each activity they were asked to describe the sorts of objects and places that were involved.

Activity 2 – Self-powered sensors and objects/places. To introduce the notion of energy-harvesting we first demonstrated a range of off-the-shelf devices (such as a hand-cranked radio). Participants were then provided with the set of harvesters-cum-sensors shown in Fig. 3, and asked to associate them with any of the objects/places mentioned in Activity 1.

Activity 3 – The quantified home. We explained how the pairing of objects/places and sensors could be used to surface the "quantity" of meaningful activities participants had identified. During this activity, we showed the example pod and clock displays and presented a role-play (by two of the researchers) showing how the system might work (see Fig. 4). Participants were asked to comment on and respond to this proposition, prompting them to consider how they would use the outputs; how the approach relates to other ways they reflect on their daily life; and, any changes to the design to make it more useful and/or effective.

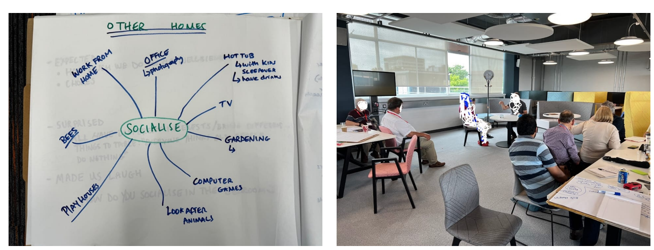

Figure 4: Left: Example artefact from Workshop II Activity 1. Right: role-play with Fig. 3 (h–i) displays

After the workshop we used a deductive approach to thematic analysis [5]. The first author organised the data collected in notebooks and flip-charts. They then applied the codes and themes of Workshop I. Following this, authors one and two reviewed the codes and searched for any new emerging themes, presenting them to the wider team for refinement.

3.3.1 Findings.

Activity 1 – The life of the home. As in Workshop I, this activity surfaced a very wide range of home activities from chores such as ironing and cooking in the kitchen to crafting and knitting in the living room. While some objects were used in multiple contexts (e.g., everyday coffee coasters for use on one's own and when socialising), others had a special purpose (e.g., *"I keep my good plates in the dining room dresser and keep them for best"*). While some participants had large homes with many rooms, others had much smaller spaces. These physical constraints led to differences in what might signify the start of an activity – for instance, one participant had only one living room and kept her crafts in one box and puzzles in another; in contrast, another had a large home with a specific room for photography and another for jigsaw puzzles.

Activity 2 – Self-powered sensors and objects/places. Participants found the multipurpose kinetic-energy switch sensor and specialised sensors (the hydro- and thermo-electric ones) the easiest to associate with objects (binary state objects for the switch – e.g., drawers and doors that open/close and a walking aid that was on or off the floor; and, taps and heat sources such as heaters, for the hydro- and thermo-electric respectively). The PV sensors were also associated with objects that could exhibit two states (e.g., an open or closed door) and the pressure sensor was mainly discussed in regards to surfaces participants would walk over such as stairs, but one group discussed its use within object handles that were grasped.

Activity 3 – The quantified home. This activity provoked a wide discussion of how the participants made sense of activities. Many had activity trackers (such as Fitbits) and one had a wearable blood sugar monitor. In addition, others mentioned the use of diaries and journalling to create richer reflections on their day. Others spoke of looking back over physical and digital calendars to remember past events. Turning to comments on the concept design, two common themes were seeing the approach as a way to reflect on how they were using their time, provoking changes if something they had enjoyed previously (e.g., a hobby) was seemingly neglected; and, for pure curiosity without specific purpose (e.g., counting the number of times they opened the fridge door). As we had explained that the pod displays were to be placed in spaces that visitors might occupy (e.g., the living room), participants were keen to ensure the visualisation was low in granularity; several participants suggested alternative surfaces that were routinely used numerous times a day to present the data: e.g., cupboards, entrance doors and as fridge magnet type objects. There was also interest in going beyond the simple displays to provide more detailed presentations which would be for their private use.

4 Implementing the concept design

Using the findings from the workshop, through a series of technical design sessions involving the author team, we refined the system in terms of the sensor specifications, activity categories and visualisations.

4.1 Sensors

Sensors were designed to be placed in and on the locations and objects associated with meaningful activities identified in Workshop II. As we are aiming at a toolkit of sensors and displays that can be used as flexibly as possible, we decided to focus on energy-harvesters-cum-sensors that had the widest range of applicability; i.e., the kinetic energy switch sensors; photovoltaic (PV) surfaces; and, the PV passive infrared sensor (see findings from Activity 2, above). Figure 5 (left) shows this set of sensors. We detail each, below, to enable replication.

Figure 5 **(a) Kinetic energy switch sensor** – used to detect the opening and closing of drawers and doors. The kinetic energy switch consists of an EnOcean PM220 Energy Converter Module for Motion Energy Harvesting to Power PTM 535BZ BLE. Each PM220 activation generates between 120 to 210 μJ @ 2V, providing sufficient power to the PM535BZ BLE transmitter module for a single wireless transmission. The PTM535BZ is configured as a BLE beacon with a transmit power of 4 dBm (2.5 mW). The kinetic energy switch sensor is contained within a 3D-printed housing. The sensor is placed near an actuated area, e.g., doors and drawers, then an acrylic "finger" is positioned so that it flips the switch of the energy converter module when the state of a door/drawer changes.

Figure 5 **(b) PV sensor** – used to detect the presence of light within storage boxes or cupboards; and to register if a light is turned on or off by placing the sensor within a lamp covering. The PV sensor used is the Cypress CYALKIT-E03 Solar-Powered BLE Sensor Beacon. The PV Sensor is powered by ambient light falling on a 15 mm × 15 mm amorphous silicon solar module and charging a 400 μF storage capacitor and 0.2 F supercapacitor via an S6AE103A energy power management IC. The beacon is set to demo mode, meaning that the transmission interval varies with ambient light level (illuminance). The beacon operates at a minimum illuminance of 100 lux (100–150 lux is the illuminance in a typical domestic living room). The BLE transmit power is configured to 0 dBm (1 mW), with the time interval between BLE transmission being anywhere between 3 seconds (illuminance of 1000 lux) to 50 seconds (illuminance of 100–200 lux) depending on illumination.

Figure 5 **(c) PV bookmark sensor** – used to detect when a book is being read by pinging when it detects the presence of light. The motivation for building this sensor was that reading was an important hobby for many of the Workshop II participants. The PV Bookmark is created by modifying a Cypress CYALKIT-E03 Solar-Powered BLE Sensor Beacon. The CYALKIT-E03 sensor only works when the solar module is facing towards the light, meaning that the user would have to ensure that the bookmark surface with the solar module was always placed facing up. To overcome this burden on the user, a bi-directional solar module is used. The original solar module is removed from the CYALKIT-E03, and then two back-to-back modules are soldered in its place. This modification allows the PV Bookmark Sensor to be placed either way up.

Figure 5 **(d) PV passive-infrared movement detector** – used to detect movement in well-lit areas. The movement sensor is made of several components. A passive-infrared (PIR) sensor to detect the movement of a person occupying the area, an InPlay IN100 BLE beacon to transmit when detection occurs, and an Epishine LEH3 Organic PV Module to harvest and provide energy. InPlay IN100 NanoBeacon Bluetooth Low Energy Beacon allows the attachment of different forms of trigger modules. We used a Panasonic PIR sensor EKMB1107112 to detect the presence of a person and trigger the NanoBeacon. The NanoBeacon is powered by an Epishine Organic

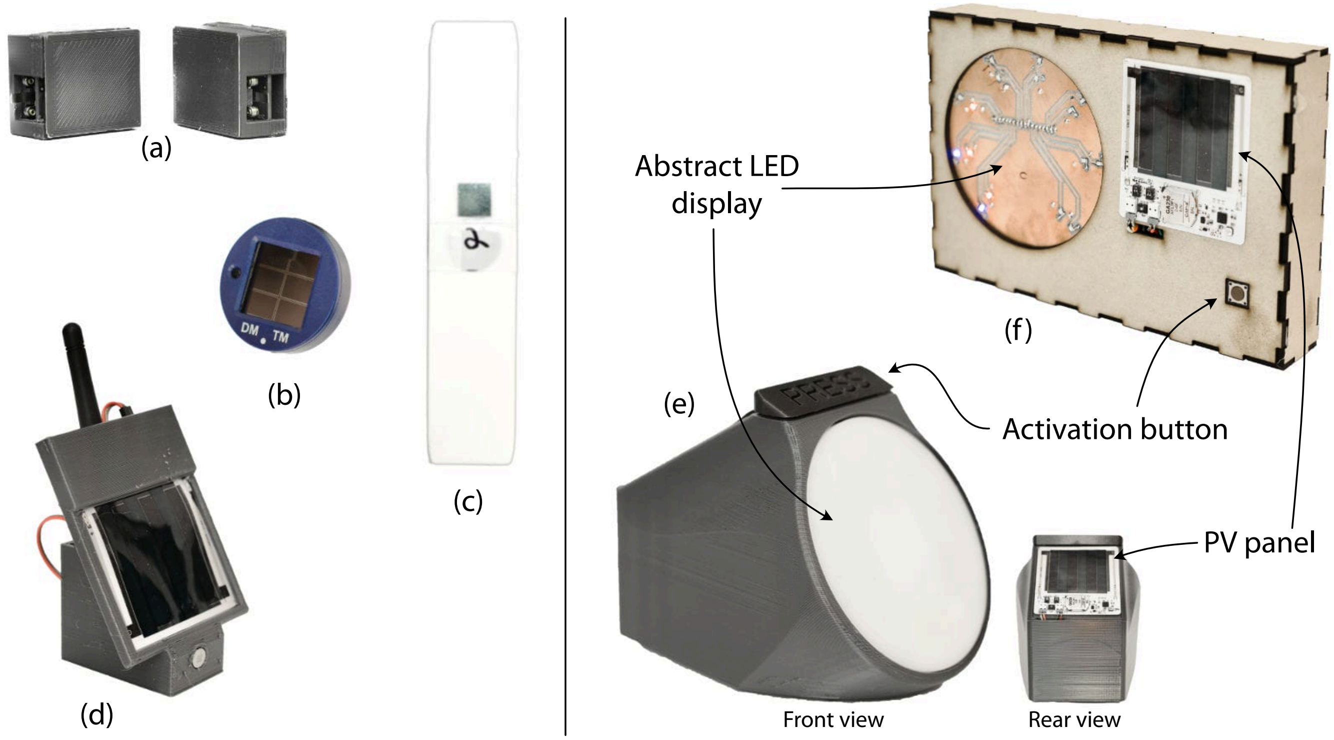

Figure 5: The Ageing Well toolkit. Left: Four sensors track everyday activities: (a) kinetic-energy switch, to detect the opening/closing of drawers or doors; (b) PV sensor, to detect when light is present in storage boxes or cupboards (i.e., they have been opened); (c) PV bookmark sensor, which can detect when it is (or is not) placed inside a book; and, (d) PV passive-infrared movement detector, detecting presence in well-lit areas such as a home office or kitchen. Right: Two self-powered displays provide insight into activity in categories: (e) pod, displaying "Hobbies/Recreation/Socialising" or "Admin/Chores"; and, (f) fridge magnet, showing "Cooking/Eating" activity. Full details on how to build and deploy the system are provided in the source code repository for this paper.[6]

Photovoltaic module. The NanoBeacon consumes less than 500 nA in sleep mode while the EKMB1107112 has a quiescent current consumption of only 1 μA. IN100 transmit power is configured to 0 dBm (1 mW). The IN100 is configured to transmit as an iBeacon. The supercapacitor (5 V, 0.4 F) of the Epishine Organic PV module will become fully charged under 500 lux illuminance in approximately 5 hours. The total charge stored in the supercapacitor is 0.4 F * 5 V = 2 C. Each IN100 trigger and BLE transmission consumes approximately 13.65 μC (measured using Nordic NRF PPK2 Power Profiler Kit). This figure is negligible in terms of our deployment scenarios. These components are then confined within a custom 3D-printed housing allowing the PIR sensor to observe an area, harvest light energy, and for the IN100s antenna to protrude.

Each sensor transmits a Bluetooth low-energy (BLE) "ping" when activated (i.e., as little information as possible, to avoid any privacy-intruding data). These pings are detected and processed by a Raspberry Pi model 4B+ running the Raspberry Pi OS Lite, as no user interface is required. The Raspberry Pi runs a Python script which constantly monitors the existence of local Bluetooth devices and checks the MAC addresses of the Bluetooth devices against a list of known MAC addresses. Then, if a match is found, a sensor has transmitted a "ping", signalling that an interaction has occurred. Following this, the sensor ID, its associated activity and the timestamp are saved and processed.

Figure 6 illustrates a range of example locations for both sensors and displays around the home.

4.2 Presenting sensor data

In Activity 1, participants showed us that objects/spaces could be used for multiple related activities. In response, we identified three broad categories that a sensor can be associated with: "Hobbies/Recreation/Socialising"; "Cooking/Eating"; or "Admin/Chores". Given participants' desire for privacy, we chose to proceed with three low-granularity abstract LED displays to present the activity in each category. After processing the "ping" data, the Raspberry Pi broadcasts the number of LEDs the interface should illuminate via a Zigbee X2C module. From participants' suggestions we made two form factors of self-powered interface: the pod, and the fridge magnet (see Fig. 5 (right) and Activity 3, above). Each form factor consists of a custom-made LED display board, driven by an ultra-low power microcontroller MSP-EXP430F5529 and a pair of 74HC595 shift registers. Wireless communication between the pods

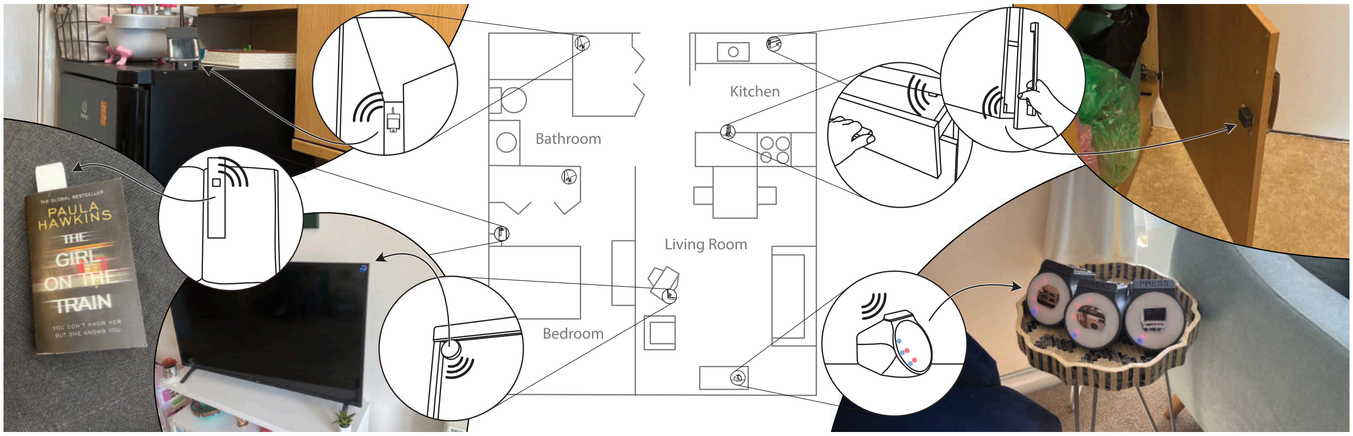

Figure 6: Example Ageing Well sensor and display locations around a home. Photo insets show actual deployments from participating households. Top left: PV passive-infrared movement detector placed on top of a participant's fridge to detect presence in the kitchen. Middle left: PV bookmark sensor inside a book on a bedside table. Bottom left: PV sensor placed in the corner of a television to detect light (i.e., its on/off status). Top right: Kinetic-energy switch attached to a kitchen cupboard to detect when it is opened or closed. Bottom right: Three self-powered pods placed upon a small table within a participant's home and labelled with photos to show the activity categories they are displaying.

and central hub is via a S2C Zigbee module. The interfaces are self-powered from ambient light energy harvested by the Epishine Organic Photovoltaic modules discussed above. The total current consumption of the interfaces in sleep mode is approximately 4.29 μA @ 3.3 V.

The display of each interface consists of two circular rings of LED lights. The inner ring shows the average of an activity calculated since activation, and the outer ring shows the count of an activity for the current day. Each interface has an activation button which, when pressed, illuminates the LEDs to show both today's level of activity and the user's overall average given the data provided by the Raspberry Pi. Once activated, the interface wakes from sleep mode, listens for the number of LEDs it should illuminate, illuminates the LEDs and then returns to its low-powered sleep mode within five seconds. Each interface activation consumes between 0.24 and 0.41 C, depending on the display data (i.e., number of LEDs illuminated). This means that a fully charged supercapacitor can power the interface for typically no more than 4 or 5 activations in close succession. The internal electronics are made to be identical, making production faster and easier. The form factor of housing is created depending on where the interfaces could be placed.

As some of the participants had described their use of both quantitative visualisations for fitness (e.g., graphs of step counts) and qualitative ways of tracking their lives (e.g., journalling and online calendars) we added four additional presentations to the design (see Activity 3, above). The first was the raw sensor data; the second used this raw data to create a heatmap showing the activation of each sensor over time. The third was a narrative created by a LLM (ChatGPT) from the sensor activations (cf. [10]) and the last was a ChatGPT-created structured diary and recommendations, again based on the sensor data. ChatGPT was also used in the deployment interviews to enable householders to interrogate their activity in the light of the LLM's data on home-life, ageing well, etc. To provide the data needed for these presentations, the object/location of each sensor (e.g., "fridge door") is defined by the user on installation and stored securely. While the pods were available to the participants throughout the deployments, the other data presentations were generated by the researchers and shown to them during the structured interviews (see Section 5.1). Figures 7 and 8 illustrate the raw data and heatmaps using data from the deployments. Box 1 (below) is an example extract from a ChatGPT story generated by the prompt, *"Write a story of X's day given these IoT sensor activations. X is a lady in her 60s"*, along with the raw data list for the period in question.[5]

Box 1:
In the cosy one-bedroom flat nestled on the fourth floor of a charming block of flats, lived X, a woman in her early 60s [. . .] Monday morning arrived, bathing X's living room in a soft golden glow as the sun's rays filtered through the sheer curtains. Her worn yet welcoming furniture seemed to come alive in the morning light, and the faint hum of the kettle indicated the start of another day [. . .]

Box 2 is an example of the structured diary and recommendations generated by the prompt *"Analyse and produce a diary of the week in a friendly format suitable for X and Y to read (this may include predicted meal times, etc., and make assumptions for activities that were ongoing between sensor readings. Note that it may be more suitable to focus on general time periods instead of exact seconds and minutes). Put it into a format which X and Y would find helpful and interesting. Perhaps it could include some recommendations or feedback on their routines, etc."*

[5]Note: names have been removed from this and other examples to preserve privacy.

Box 2:
Patterns & Observations:
1. Leisure and Reading: Your dedication to reading was evident, with regular reading sessions both early in the morning and in the evenings. These moments allowed you to unwind and enjoy personal time.

[. . .]

Recommendations:
1. Efficient Kitchen Organisation: To streamline your kitchen activities, consider reorganising cupboards and drawers for easy access to utensils, pans, and cleaning supplies.

[. . .]

4. Hydration and Breaks: With your busy routines, remember to stay hydrated and take short breaks to maintain your energy levels throughout the day.

To support and enable others to build upon this work, full details of the toolkit are provided in the accompanying source code repository for this paper[6].

5 Deploying the system

We recruited two households who allowed us to install the system for a total of six weeks of deployment.

5.1 Method

Household 1 (H1) consisted of a single female (age 67)—P1—who lived in a small apartment with an open-plan kitchen combined with a living room, one bedroom, hallway and bathroom. P1 looked after her grand-daughter at home several times each week. P1 had participated in Workshop I and self-identified as someone who enjoyed tracking elements of her daily life. Household 2 (H2) were a married couple (male and female, average age 72)—P2 (M) and P3 (F)—who had lived in this large 1901 townhouse for 48 years. The house had three floors with multiple rooms including a "book room". In contrast to P1, neither of the participants had previously taken part in either of the two workshops, and neither used any form of digital self-tracking.

H1 had the system deployed for four weeks and H2 for two weeks. During this period, we visited each household several times to carry out interviews and extract data from the deployed system for further analysis.

Installation. For the three activity categories described earlier ("Hobbies/Recreation/Socialising"; "Cooking/Eating"; and, "Admin/-Chores"), the householders were asked to walk us through relevant locations and objects. Twelve sensors were then attached to the objects and locations and each was associated with one of the three pod and fridge magnet displays. That is, each home had two displays (a pod and a fridge magnet) for each of the three activity categories. The system was tested and demonstrated to the householders.

Follow-up 1. After a week, we returned to the households and carried out a structured interview that probed participants to reflect on the system and its use. We also addressed any technical or design aspects.

[6] https://github.com/fitlab-swansea/ageing-well-toolkit/

```
23-08-2023, 08:21:59, Utensil Drawer
23-08-2023, 08:25:07, Kitchen
23-08-2023, 08:26:16, Toybox
23-08-2023, 08:26:24, Kitchen
23-08-2023, 08:26:51, Utensil Drawer
23-08-2023, 08:27:03, Bin Cupboard
23-08-2023, 08:29:19, Kitchen
23-08-2023, 08:55:33, Utensil Drawer
23-08-2023, 09:04:11, Kitchen
23-08-2023, 09:49:50, Toybox
23-08-2023, 10:53:05, Bin Cupboard
23-08-2023, 10:53:09, Kitchen
23-08-2023, 10:58:51, Toybox
```

Figure 7: An extract from the raw data logs captured from a participating household during our deployment.

Follow-ups 2–4. At one-week intervals we returned to H1 (days 7, 14, 21 & 28) and H2 (days 7, 14) to seek further responses, again using a structured interview technique.

Interrogating alternative visualisations. The four alternative visualisations described earlier were constructed from the sensor data gathered for the household to date on days 14, 21 & 28 (H1); and, 14 & 21 (H2). These visualisations were shown to the householders during three (H1) and two (H2) visits to their homes, and as well asking them to respond to the presentations, for the LLM we asked participants to construct prompts that could further interrogate the data to generate additional LLM interpretation and output.

Both quantitative data (e.g., display activations) and qualitative data (interview transcripts) were collected during the study. In a similar fashion to prior work (e.g., [2]) we analysed the interview transcripts using a mixed bottom-up (free of the themes surfaced in the co-creative processes) and top-down (using themes such as privacy and curiosity) approach.

5.2 Findings

Sensor placement. The sensor activity-agnostic design was beneficial as a wide range of different objects and locations were identified by participants. These included drawers, lid boxes, doors, living and kitchen areas. The need for customisation was surfaced, though, by a request from P1 who wanted a PV sensor on her grand-daughter's toy box; however, due to concerns about potential choking hazard if the sensor was deployed as standard, we provided a customised 3D-printed safety container. The simple-to-configure and editable nature of our toolkit supports the sorts of adjustments home-owners might request after initial deployments: e.g., after seven days of using the system, P1 asked for an additional sensor to be placed on her recycling bins, and P3 suggested that a sensor to log her use of the telephone would be helpful as she did most of her socialising by chatting on the phone.

Display activation. On average, H1 and H2 pressed the pod buttons three times a day. A similar pattern was seen with respect to the fridge magnet displays.

Reflections on home-use. For H1 and H2 participants found that the system did prompt them to consider their use of the home. P1 told us that her awareness of the system—not simply the output displayed by the pods—caused her to reflect on her home life (e.g., *"Just having it here is making me think more of what I do around*

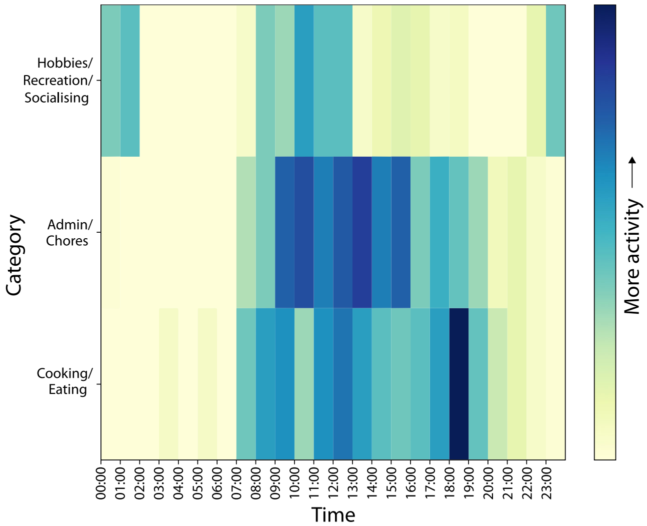

Figure 8: A sample heatmap created from 20 days of household object/activity data and used as a one of the visualisation options to stimulate reflection on home use.

the flat"). For instance, the mechanical noise the kinetic-energy sensors made in her kitchen reminded her that she had left her television on, so she went to switch it off while cooking. P1 also gained insight into her leisure time (e.g., in a self-judgmental tone, *"I read less than I thought I did [...] I have been binge-watching a series on telly"*). H2 reported that the system led them to reflect that they had a fixed routine they were comfortable with (e.g., P2, *"We have a ritual that we do every day"* and *"We are not going to change at this point in life"*). The system, then, provides both possibilities of provoking action and changes, and acts as a reminder or signifier of the "pulse" of the home.

Alternative presentations. The raw data and heatmaps stimulated H1 and H2 to proactively discuss and reflect on their home use, inferring activities that were signalled by sensors directly and indirectly associated with the activity: e.g., *"That was me in the kitchen making tea past midnight on Tuesday"* (P1); and, from sensors attached to cutlery drawers and crockery cupboards but not the dishwasher, *"We are obviously unloading the dishwasher then"* (P2 & P3).

The ChatGPT-generated stories were received well in three regards. Firstly, for H2 the stories were entertaining and caused reflections on their actual and ChatGPT-imagined lives: e.g., *"What an exciting life we lead!"*; and, in response to a generated passage that said the couple danced into the night in the kitchen, *"My partner doesn't dance until [they have] had five pints"*. Secondly, for H1, the apparent accuracy of stories was surprising: e.g., there was a passage about a "worn linoleum floor" (despite there being no prompt to ChatGPT about the floor, its material or condition) and P1 told us that they had indeed been aware of the condition of their floor. Thirdly, both H1 and H2 encountered ChatGPT output that surfaced limitations and issues associated with generative AI: in addition to the co-incidental truths generated (such as the previous example), P2 and P3 noted the sexism in the story language, as ChatGPT consistently placed the female character in the kitchen or doing chores.

H1 and H2 preferred the structured diary style output generated by ChatGPT over the story format, and found the recommendations insightful and useful: e.g., for H1, ChatGPT suggested the participant to be more organised in the kitchen based on multiple instances of opening and closing the same cupboards. P1 liked this as they believed the system had surfaced something she had been pondering herself. For H2, the system recommended installing a motion-sensing light in the kitchen. Both participants found such a suggestion useful, as they often left the kitchen light on for long periods having forgotten to turn it off. H1 and H2 were able to suggest additional prompts to interrogate the data (e.g., *"Tell me when I eat meals"* (P1); and, *"What do we normally do around 11 AM?"* (P2 & P3). Of the different presentations, both households felt the LLM ones provided the most potential for deepening their understanding and enjoyment of their home.

Concerns and limitations. Both H1 and H2 told us that visitors had raised privacy concerns (e.g., H1: '*'Can they hear us? [...] Can they see us?"*). H2's home was large and the walls thick; this led to some issues for the BLE communications. Further, the home due its older design and the homeowners' choice of lighting was challenging for the photovoltaic energy harvesters. No such issues were found in the modern, light-filled home of H1.

5.3 Technical findings and adaptations

As well as useful insights from homeowners, the process of deploying the system within the homes has also enabled us to understand technical limitations and missed opportunities. We detail these, below, and show how we have adapted the toolkit in response.

Figures 9 and 10 illustrate prototypes of the adaptations: drawer/door sensors designed to fit on top standard drawer/door fittings; similarly, a light-switch-based sensor to sit over home switches; a roller-blind fitting sensor to enable the system to capture openings and closings of window coverings; and, a heat-actuated sensor based on a greenhouse autovents system[7] enabling us to register changes to room temperatures if, for instance, attached to a home radiator.

Turning first to the drawer/door fitting. In the toolkit described in this paper, the kinetic energy sensor requires two parts: the sensor itself and a "finger" of acrylic to actuate the switch. This setup allowed an almost universal use of the kinetic energy switch. However, this involved precise positioning of both parts. Following the deployments, further iterations of the kinetic energy sensor were developed. These iterations took inspiration from the furniture and accessory manufacturer IKEA. IKEA products are known for their simplicity and compatibility. Using these inspirations, we began development on two kinetic sensor versions – the kinetic door sensor and the kinetic drawer sensor

The kinetic door sensor builds on the IKEA Utrusta push-to-open accessory[8]. The sensor component attaches to a cupboard, near the door (see Fig. 9 (a)). The sensor uses a spring-based device to trigger the kinetic sensor without an acrylic "finger", making installation

[7]A mineral wax linear actuator: https://harvst.co.uk/how-do-automatic-greenhouse-window-openers-work

[8]https://www.ikea.com/gb/en/p/utrusta-push-opener-80230224/

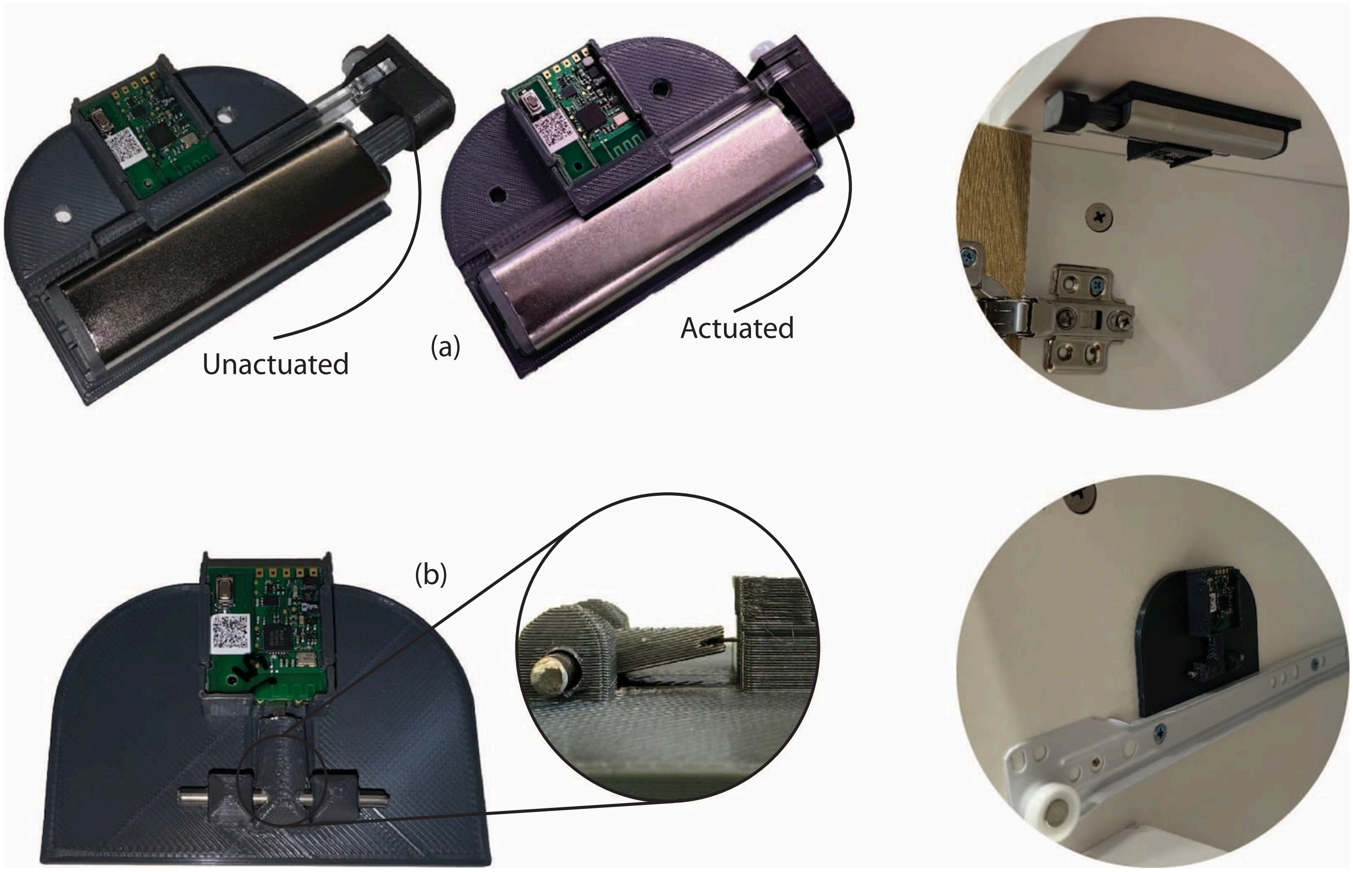

Figure 9: Prototype toolkit adaptions: (a) the kinetic door sensor in actuated and unactuated states, and (right) in situ. (b) the kinetic drawer sensor, with its mechanism detail enlarged, and (right) in situ.

more robust and easier to carry out. When the door is opened, the spring triggers the switch, and when the door is closed the door pushes back the trigger to activate the switch once again.

The kinetic drawer sensor, meanwhile, is based on the IKEA Markhus soft closing device[9]. The purpose of the device is to stop a drawer from slamming shut. It performs its task by dampening the linear movement of the drawer. We have been inspired by this mechanism so that instead of dampening the drawer's linear movement, it triggers the kinetic energy switch. Figure 9 (b) shows the kinetic drawer sensor, and the sensor in situ. Unlike the Markhus device, our sensor only needs a momentary connection with the moving drawer. This contact occurs when the drawer begins to open, and again when it is about to close. This adaptation creates a more robust method of activation and simplifies installation.

In the existing toolkit, lights being turned on and off are monitored using photovoltaic sensors placed within a lamp covering. However, this is suboptimal as continuous "pings" from these sensors are received when the bulb is on. To address this problem, we developed a 3D printed housing which can be retrofitted to existing wall-based light switches. Placement of the light-switch sensor requires no knowledge of electrical wiring as it does not alter the existing switch. The sensor is simply placed over the existing switch. The light-switch sensor looks and works the same way as the existing switch. In addition, the sensor incorporates a kinetic energy sensor switch to "ping" when the switch has flipped. Figure 10 (a) shows a single light-switch sensor. Double and triple light-switch sensors have also been developed for use where needed. The sizing of wall-based light switches is standardised, allowing generic sensors.

Another additional sensor placement identified during the deployments was a roller blind. These fittings often exist in more than one room within a home, and may be raised or lowered throughout the day via a pull cord. Roller blinds usually have either a 28mm or 32mm diameter pole, with the mechanism being universal. The mechanism consists of a static core, which is attached to the bracket, and a rotating outer collar, which is rotated by the pull cord to allow the raising and lowing of the blind. We have created a mechanism to convert this rotational movement into energy to "ping" when the roller blind is being raised or lowered. The mechanism connects to the static core, housing a geared motor. A disc is connected to the driveshaft of the motor, which is locked into place within the pole of the blind (using the point at which the blind material is connected to the pole). A PTM 535BZ BLE device is placed outside

[9] https://www.ikea.com/gb/en/p/markhus-soft-closing-device-60426571/

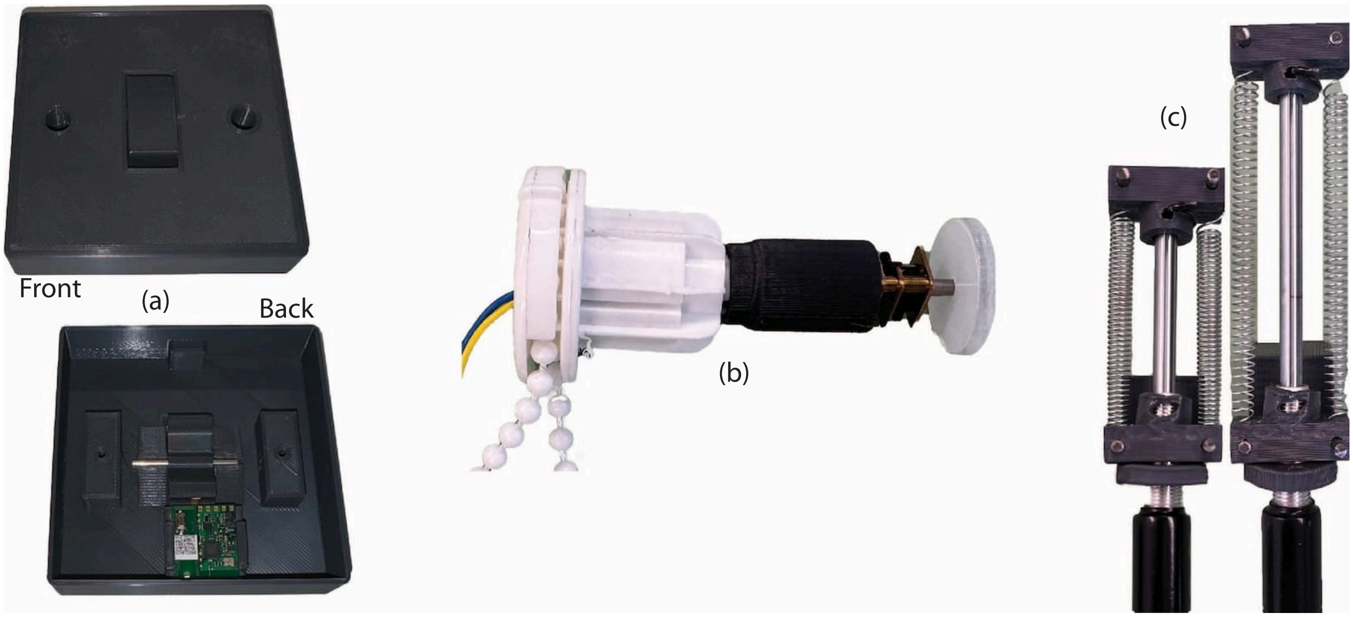

Figure 10: Prototype toolkit additions: (a) the light switch sensor. (b) the roller blind sensor mechanism. The white section is a standard roller blind mechanism, and the dark grey section houses the geared motor. The left of the mechanism shows the wire connections, while the right shows the disc connected to the motor driveshaft. (c) the heat based sensor prototype in its cool (left) and warm (right) states.

of the roller blind (as the metal pole blocks its signals). The device is powered by the mechanism using wires through the static core. Figure 10 (b) shows the roller blind mechanism.

Finally, development has begun on self-powered heat-actuated sensors. Mineral wax linear actuators are used to “ping” when a room reaches a predetermined temperature. Originally, these mineral wax linear actuators opened and closed greenhouse openings to reduce the internal heat. A housing developed to hold the kinetic sensor and a spring-based mechanism will allow the adjustment and activation at a chosen temperature. Figure 10 (c) shows the prototype heat-actuated sensor and its mechanism.

6 Discussion

There is a clear opportunity to explore IoTs that embody framings beyond the orthodox ageist, decline-focused models which dominate the research literature and commercial system offerings. The findings of our design workshops and deployments evidence a range of ways for such framings to support home-life and reflection.

Workshop I provoked a re-examination of monitoring in the light of the diversity of positive home activities our participants described. In addition, participants emphasised the need for any system to prioritise both privacy and low energy costs. These requirements directly influenced the initial concept design involving self-powered components and privacy-preserving communications. The proliferation of IoT home systems—for older adults and indeed homeowners in general—has led to many concerns around privacy, security and energy costs. Participants’ views and the system designs they helped shape in our work are ones we would strongly encourage all home IoT developers to consider.

In Workshop II the rich descriptions of how participants used their homes and the ways they currently reflect on their daily lives led to an extensible novel toolkit. During the subsequent deployment the combination of IoT sensor data with ChatGPT, spurred by participants’ journaling practices, also demonstrated a novel use of LLMs.

As a side-effect, we note too that using the LLM in regards to their own home-life provided an accessible and creative—rather than an abstract or hyped—way for our participants in the deployment to learn about generative AI and its limitations. While the ChatGPT-generated reflections and recommendations might seem at odds with one of our initial design drivers—namely to provide ways for homeowners to make their own meanings—we saw that these outputs spurred reflections and further questions rather than turning the participants into passive consumers of monitoring outputs. The deployment combined both user centred and technology-centred perspectives; in doing so we gained insights to steer our technical innovations and use-cases.

7 Limitations

Two of the requirements for the system design from the older adult participants were privacy-preserving qualities and low energy needs. We acknowledge that an LLM requires a great deal of energy when it is being trained. However, we are simply making use of an existing resource that exists regardless of our application. We note ongoing efforts to reduce the carbon impact of such systems (e.g., [8]). We further acknowledge that transmitting the sensor data to an external LLM (like ChatGPT) could risk privacy invasion. However, given the lack of location data and the generic object descriptions (e.g., "puzzle box") transmitted, we feel the threat to privacy is very low. Nevertheless, we are considering removing the need to use an external LLM through a locally deployed model[10].

Our focus in this work was "ageing well", and our older adult participants were committed to positive perspectives on ageing. We acknowledge there are many older adults who have to deal with many physical and cognitive issues as they age. We did not shape or evaluate the proposals presented here in these contexts: existing IoT systems are predominately designed to support "frailty". We might speculate, though, that older adults dealing with such issues would be additionally served by the sort of systems proposed in this paper as well as by conventional monitoring services.

8 Conclusions and future work

The older adults we worked with in this project were "ageing well" and did not see the value of commercially available and previous research IoT prototypes that attempt to watch over or protect them. In contrast, they articulated a desire to use new technologies to help them flourish. This desire to grow as they aged was demonstrated by the range of activities and interests they shared with us. The IoT they helped design, then, spoke to their curiosity and eagerness to reflect and learn. With the evidence provided by the focused deployments, we plan to provide householders with much larger numbers of sensors (from the current 12 to 60+) they can use to instrument their house, with the hypothesis that this will enable broader and deeper insights into home life. In terms of displaying the outputs of these sensors, given the interest and value in LLMs, we plan to explore this approach further including the use of self-powered E Ink displays to provide the sorts of narrative and structured summaries explored in these first studies.

Acknowledgments

We would like to thank Swansea Ageing Well, workshop participants and the homeowners who enabled our deployments. This work was supported by Engineering and Physical Sciences Research Council grant EP/W025396/1.

References

[1] Aloha Hufana Ambe, Margot Brereton, Alessandro Soro, Laurie Buys, and Paul Roe. 2019. The Adventures of Older Authors: Exploring Futures through Co-Design Fictions. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland, UK) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–16. https://doi.org/10.1145/3290605.3300588

[2] Aloha Hufana Ambe, Margot Brereton, Alessandro Soro, Min Zhen Chai, Laurie Buys, and Paul Roe. 2019. Older People Inventing Their Personal Internet of Things with the IoT Un-Kit Experience. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland, UK) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3290605.3300552

[3] Joseph Aneke, Carmelo Ardito, Danilo Caivano, Lucio Colizzi, Maria Francesca Costabile, and Loredana Verardi. 2018. A Low-Cost Flexible IoT System Supporting Elderly's Healthcare in Rural Villages. In *Proceedings of the Second African Conference for Human Computer Interaction: Thriving Communities* (Windhoek, Namibia) *(AfriCHI '18)*. Association for Computing Machinery, New York, NY, USA, Article 24, 4 pages. https://doi.org/10.1145/3283458.3283470

[4] Abul Al Arabi, Xue Wang, Yang Zhang, and Jeeeun Kim. 2023. E3D: Harvesting Energy from Everyday Kinetic Interactions Using 3D Printed Attachment Mechanisms. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 7, 3, Article 84 (sep 2023), 31 pages. https://doi.org/10.1145/3610897

[5] Virginia Braun and Victoria Clarke. 2021. *Thematic Analysis: A Practical Guide.* Sage, London, UK.

[10] For example, Ollama: https://ollama.com/

[6] Tim Campbell, Eric Larson, Gabe Cohn, Jon Froehlich, Ramses Alcaide, and Shwetak N. Patel. 2010. WATTR: A Method for Self-Powered Wireless Sensing of Water Activity in the Home. In *Proceedings of the 12th ACM International Conference on Ubiquitous Computing* (Copenhagen, Denmark) *(UbiComp '10)*. Association for Computing Machinery, New York, NY, USA, 169–172. https://doi.org/10.1145/1864349.1864378

[7] Eli Carmeli, Hagar Patish, and Raymond Coleman. 2003. The Aging Hand. *The Journals of Gerontology: Series A* 58, 2 (02 2003), M146–M152. https://doi.org/10.1093/gerona/58.2.M146

[8] Andrew A Chien, Liuzixuan Lin, Hai Nguyen, Varsha Rao, Tristan Sharma, and Rajini Wijayawardana. 2023. Reducing the Carbon Impact of Generative AI Inference (Today and in 2035). In *Proceedings of the 2nd Workshop on Sustainable Computer Systems* (Boston, MA, USA) *(HotCarbon '23)*. Association for Computing Machinery, New York, NY, USA, Article 11, 7 pages. https://doi.org/10.1145/3604930.3605705

[9] Elaine Czech, Ewan Soubutts, Rachel Eardley, and Aisling Ann O'Kane. 2023. Independence for Whom? A Critical Discourse Analysis of Onboarding a Home Health Monitoring System for Older Adult Care. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 330, 15 pages. https://doi.org/10.1145/3544548.3580733

[10] Audrey Desjardins, Heidi R. Biggs, Cayla Key, and Jeremy E. Viny. 2020. IoT Data in the Home: Observing Entanglements and Drawing New Encounters. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376342

[11] Eric Dishman. 2004. Inventing Wellness Systems for Aging in Place. *Computer* 37, 5 (may 2004), 34–41. https://doi.org/10.1109/MC.2004.1297237

[12] Emma Dixon, Anne Marie Piper, and Amanda Lazar. 2021. "Taking Care of Myself as Long as I Can": How People with Dementia Configure Self-Management Systems. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 656, 14 pages. https://doi.org/10.1145/3411764.3445225

[13] Ezequiel Duque, Guilherme Fonseca, Heitor Vieira, Gustavo Gontijo, and Lucila Ishitani. 2019. A Systematic Literature Review on User Centered Design and Participatory Design with Older People. In *Proceedings of the 18th Brazilian Symposium on Human Factors in Computing Systems* (Vitória, Espírito Santo, Brazil) *(IHC '19)*. Association for Computing Machinery, New York, NY, USA, Article 9, 11 pages. https://doi.org/10.1145/3357155.3358471

[14] Hassan Elahi, Khushboo Munir, Marco Eugeni, Sofiane Atek, and Paolo Gaudenzi. 2020. Energy Harvesting towards Self-Powered IoT Devices. *Energies* 13, 21 (2020), 31 pages. https://doi.org/10.3390/en13215528

[15] Joel E. Fischer, Andy Crabtree, Tom Rodden, James A. Colley, Enrico Costanza, Michael O. Jewell, and Sarvapali D. Ramchurn. 2016. "Just Whack It on until It Gets Hot": Working with IoT Data in the Home. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 5933–5944. https://doi.org/10.1145/2858036.2858518

[16] James Fogarty, Carolyn Au, and Scott E. Hudson. 2006. Sensing from the Basement: A Feasibility Study of Unobtrusive and Low-Cost Home Activity Recognition. In *Proceedings of the 19th Annual ACM Symposium on User Interface Software and Technology* (Montreux, Switzerland) *(UIST '06)*. Association for Computing Machinery, New York, NY, USA, 91–100. https://doi.org/10.1145/1166253.1166269

[17] John E. Kaufman. 1981. *IES Lighting Handbook.* Illuminating Engineering Society of North America.

[18] Alireza Khaligh, Peng Zeng, and Cong Zheng. 2010. Kinetic Energy Harvesting Using Piezoelectric and Electromagnetic Technologies—State of the Art. *IEEE Transactions on Industrial Electronics* 57, 3 (2010), 850–860. https://doi.org/10.1109/TIE.2009.2024652

[19] Rolf Arne Kjellby, Thor Eirik Johnsrud, Svein Erik Loetveit, Linga Reddy Cenkeramaddi, Mohamed Hamid, and Baltasar Beferull-Lozano. 2018. Self-Powered IoT Device for Indoor Applications. In *2018 31st International Conference on VLSI Design and 2018 17th International Conference on Embedded Systems (VLSID)*. IEEE, New York, NY, USA, 455–456. https://doi.org/10.1109/VLSID.2018.110

[20] Albrecht Kurze, Andreas Bischof, Sören Totzauer, Michael Storz, Maximilian Eibl, Margot Brereton, and Arne Berger. 2020. Guess the Data: Data Work to Understand How People Make Sense of and Use Simple Sensor Data from Homes. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376273

[21] Amanda Lazar, Ben Jelen, Alisha Pradhan, and Katie A. Siek. 2021. Adopting Diffractive Reading to Advance HCI Research: A Case Study on Technology for Aging. *ACM Transactions on Computer-Human Interaction (TOCHI)* 28, 5, Article 32 (aug 2021), 29 pages. https://doi.org/10.1145/3462326

[22] Yichen Li, Tianxing Li, Ruchir A. Patel, Xing-Dong Yang, and Xia Zhou. 2018. Self-Powered Gesture Recognition with Ambient Light. In *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology* (Berlin, Germany) *(UIST '18)*. Association for Computing Machinery, New York, NY, USA, 595–608. https://doi.org/10.1145/3242587.3242635

[23] Ann Light, Tuck W. Leong, and Toni Robertson. 2015. Ageing Well with CSCW. In *Proceedings of the 14th European Conference on Computer Supported Cooperative Work* (Oslo, Norway) *(ECSCW '15)*, Nina Boulus-Rødje, Gunnar Ellingsen, Tone Bratteteig, Margunn Aanestad, and Pernille Bjørn (Eds.). Springer International Publishing, 295–304. https://doi.org/10.1007/978-3-319-20499-4_16

[24] Dong Ma, Guohao Lan, Mahbub Hassan, Wen Hu, Mushfika B. Upama, Ashraf Uddin, and Moustafa Youssef. 2019. SolarGest: Ubiquitous and Battery-free Gesture Recognition using Solar Cells. In *The 25th Annual International Conference on Mobile Computing and Networking* (Los Cabos, Mexico) *(MobiCom '19)*. Association for Computing Machinery, New York, NY, USA, Article 12, 15 pages. https://doi.org/10.1145/3300061.3300129

[25] Yogesh Kumar Meena, Krishna Seunarine, Deepak Ranjan Sahoo, Simon Robinson, Jennifer Pearson, Chi Zhang, Matt Carnie, Adam Pockett, Andrew Prescott, Suzanne K. Thomas, Harrison Ka Hin Lee, and Matt Jones. 2020. PV-Tiles: Towards Closely-Coupled Photovoltaic and Digital Materials for Useful, Beautiful and Sustainable Interactive Surfaces. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376368

[26] Yogesh Kumar Meena, Xing-Dong Yang, Markus Löchtefeld, Matt Carnie, Niels Henze, Steve Hodges, Matt Jones, Nivedita Arora, and Gregory D. Abowd. 2020. SelfSustainableCHI: Self-Powered Sustainable Interfaces and Interactions. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI EA '20)*. Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/3334480.3375167

[27] Hannes Michaels, Michael Rinderle, Iacopo Benesperi, Richard Freitag, Alessio Gagliardi, and Marina Freitag. 2023. Emerging indoor photovoltaics for self-powered and self-aware IoT towards sustainable energy management. *Chemical Science* 14 (2023), 5350–5360. Issue 20. https://doi.org/10.1039/D3SC00659J

[28] Philipp Morgner, Christian Müller, Matthias Ring, Björn Eskofier, Christian Riess, Frederik Armknecht, and Zinaida Benenson. 2017. Privacy Implications of Room Climate Data. In *Computer Security (ESORICS '17)*, Simon N. Foley, Dieter Gollmann, and Einar Snekkenes (Eds.). Springer International Publishing, 324–343. https://doi.org/10.1007/978-3-319-66399-9_18

[29] William Odom, Richard Banks, Abigail Durrant, David Kirk, and James Pierce. 2012. Slow Technology: Critical Reflection and Future Directions. In *Proceedings of the Designing Interactive Systems Conference* (Newcastle Upon Tyne, UK) *(DIS '12)*. Association for Computing Machinery, New York, NY, USA, 816–817. https://doi.org/10.1145/2317956.2318088

[30] Preeyam K. Parikh, Angela K. Troyer, Andrea M. Maione, and Kelly J. Murphy. 2015. The Impact of Memory Change on Daily Life in Normal Aging and Mild Cognitive Impairment. *The Gerontologist* 56, 5 (04 2015), 877–885. https://doi.org/10.1093/geront/gnv030

[31] Alisha Pradhan, Leah Findlater, and Amanda Lazar. 2019. "Phantom Friend" or "Just a Box with Information": Personification and Ontological Categorization of Smart Speaker-Based Voice Assistants by Older Adults. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW, Article 214 (2019), 21 pages. https://doi.org/10.1145/3359316

[32] Yvonne Rogers and Gary Marsden. 2013. Does He Take Sugar? Moving Beyond the Rhetoric of Compassion. *Interactions* 20, 4 (2013), 48–57. https://doi.org/10.1145/2486227.2486238

[33] Dennis Schleicher, Peter Jones, and Oksana Kachur. 2010. Bodystorming as embodied designing. *Interactions* 17, 6 (2010), 47–51. https://doi.org/10.1145/1865245.1865256

[34] Alexander Seifert, Shelia R Cotten, and Bo Xie. 2021. A Double Burden of Exclusion? Digital and Social Exclusion of Older Adults in Times of COVID-19. *The Journals of Gerontology: Series B* 76, 3 (Feb 2021), e99–e103. https://doi.org/10.1093/geronb/gbaa098

[35] Krishna Seunarine, Zaid Haymoor, Michael Spence, Gregory Burwell, Austin Kay, Paul Meredith, Ardalan Armin, and Matt Carnie. 2024. Light power resource availability for energy harvesting photovoltaics for self-powered IoT. *Journal of Physics: Energy* 6, 1 (2024), 015018. https://doi.org/10.1088/2515-7655/ad1764

[36] Yonas Tadesse, Shujun Zhang, and Shashank Priya. 2009. Multimodal Energy Harvesting System: Piezoelectric and Electromagnetic. *Journal of Intelligent Material Systems and Structures* 20, 5 (2009), 625–632. https://doi.org/10.1177/1045389X08099965

[37] Yen Kheng Tan and Sanjib Kumar Panda. 2011. Energy Harvesting From Hybrid Indoor Ambient Light and Thermal Energy Sources for Enhanced Performance of Wireless Sensor Nodes. *IEEE Transactions on Industrial Electronics* 58, 9 (2011), 4424–4435. https://doi.org/10.1109/TIE.2010.2102321

[38] Jordan Tewell, Dympna O'Sullivan, Neil Maiden, James Lockerbie, and Simone Stumpf. 2019. Monitoring Meaningful Activities Using Small Low-Cost Devices in a Smart Home. *Personal Ubiquitous Comput.* 23, 2 (2019), 339–357. https://doi.org/10.1007/s00779-019-01223-2

[39] Nicolas Villar and Steve Hodges. 2010. The Peppermill: A Human-Powered User Interface Device. In *Proceedings of the Fourth International Conference on Tangible, Embedded, and Embodied Interaction* (Cambridge, Massachusetts, USA) *(TEI '10)*. Association for Computing Machinery, New York, NY, USA, 29–32. https://doi.org/10.1145/1709886.1709927

[40] John Vines, Gary Pritchard, Peter Wright, Patrick Olivier, and Katie Brittain. 2015. An Age-Old Problem: Examining the Discourses of Ageing in HCI and Strategies for Future Research. *ACM Transactions on Computer-Human Interaction (TOCHI)* 22, 1, Article 2 (2015), 27 pages. https://doi.org/10.1145/2696867

[41] Yi Xin, Xiang Li, Hongying Tian, Chao Guo, Chenghui Qian, Shuhong Wang, and Cheng Wang. 2016. Shoes-equipped piezoelectric transducer for energy harvesting: A brief review. *Ferroelectrics* 493, 1 (2016), 12–24. https://doi.org/10.1080/00150193.2016.1123061

[42] Xiaoying Yang, Jacob Sayono, and Yang Zhang. 2023. CubeSense++: Smart Environment Sensing with Interaction-Powered Corner Reflector Mechanisms. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology* (San Francisco, CA, USA) *(UIST '23)*. Association for Computing Machinery, New York, NY, USA, Article 78, 12 pages. https://doi.org/10.1145/3586183.3606744

[43] Dingtian Zhang, Jung Wook Park, Yang Zhang, Yuhui Zhao, Yiyang Wang, Yunzhi Li, Tanvi Bhagwat, Wen-Fang Chou, Xiaojia Jia, Bernard Kippelen, Canek Fuentes-Hernandez, Thad Starner, and Gregory D. Abowd. 2020. OptoSense: Towards Ubiquitous Self-Powered Ambient Light Sensing Surfaces. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 3, Article 103 (2020), 27 pages. https://doi.org/10.1145/3411826

[44] Yang Zhang, Yasha Iravantchi, Haojian Jin, Swarun Kumar, and Chris Harrison. 2019. Sozu: Self-Powered Radio Tags for Building-Scale Activity Sensing. In *Proceedings of the 32nd Annual ACM Symposium on User Interface Software and Technology* (New Orleans, LA, USA) *(UIST '19)*. Association for Computing Machinery, New York, NY, USA, 973–985. https://doi.org/10.1145/3332165.3347952