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Detecting the Impact of Older Adult Healthy Brain Aging Behaviour Adoption Using Smart Home Technology

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Abstract – Adopting healthy brain behaviours may enhance and sustain cognitive health for older adults at risk of cognitive decline. Because relying on laboratory measures or self-report to assess the impact of a behaviour change is prone to error, we introduce a method to monitor, quantify, and describe behaviour change using smart homes. In this paper, we describe the application of this method to analyse behaviour change for n=14 older adults receiving a six-week healthy brain behaviour program consisting of personalized education, selection, and monitoring of new, sustainable healthy brain aging behaviours. A CASAS Smart Home in a Box (CASAS ShiB) is installed in each participant's home and data are collected continuously at baseline and during the program. Using our Behaviour Change Detection (BCD) algorithm, we quantify weekly changes in behaviour at baseline and each program week. Across the study population, results show that behaviour change from baseline to the end of program represents a 23.22% increase in change within the four-week baseline. We employ a virtual classifier to analyze the type of changes that are observed and assess them in comparison with self-reported goal adherence. The results indicate that smart home technologies combined with data mining techniques provide a method to monitor and support behaviour change goals in everyday life.

Keywords**:** smart home, digital behaviour markers, behaviour change, cognitive health, healthy behaviours, aging

1. Introduction

The global increase in the prevalence of Alzheimer's and related dementias (ADRDs) is a complex social challenge. More than 55 million people world-wide are living with dementia, a syndrome leading to cognitive decline caused by various diseases that damage or destroy the brain's nerve cells, with nearly 10 million cases added annually [1]. Dementia is a major cause of disability and dependence among older adults [1], [2]. A high proportion of persons with dementia are cared for at home yet the number of caregivers remains disproportionate to the need [3], [4]. Addressing the complexity of this global situation has shaped global health priorities. Evidence-based interventions aimed at combating cognitive decline are needed.

It has been estimated that one-third of dementia cases are attributable to modifiable risks, including physical inactivity, depression, and lack of cognitive stimulation [5]. In the absence of effective pharmaceutical therapies, reducing these risks is key to maintaining connection to friends and family and extending independent living, which many older adults desire [6]. A body of evidence shows the potential for brain neuroplasticity not only in response to cognitive stimulation but also social engagement, exercise, and cognitively stimulating leisure activities [7], [8]. Programs that support brain health by targeting risk factors and promoting behaviour change are of interest to the community [9], [10]. Recent data suggests that multi-domain brain health programs show promise for increasing engagement in healthy brain aging behaviours and improving cognitive outcomes [11], [12]. At the same time, obtaining scientific evidence that healthy brain aging behaviours are being effectively integrated into an individual's everyday routines to support cognition and functional independence is difficult to achieve as traditional methods of assessing outcomes rely on sparse sets of clinical measures obtained in controlled settings.

Smart homes may offer an opportunity to gain objective information about engagement in healthy brain activities through continuous monitoring of a person's behaviour. Because ambient sensor data are collected unobtrusively, the assessed behaviour changes hold greater ecological validity than laboratory measures and self-report. In this paper, we introduce a smart home technology to monitor, quantify, and describe weekly behaviour change in the context of a brain behaviour program. Contributions of this work include application of a brain behaviour program personalized for each participant's needs and schedule; smart home technology to monitor behaviour patterns; behaviour change detection algorithm to quantify and describe changes in behaviour from baseline; and analysis of goal adherence and changes for a cohort of n=14 older adults. This study was approved for human subjects' research by the Washington State University Institutional Review Board.

2. Related Work

2.1. Home-Based Interventions for Dementia

Non-pharmacological interventions administered in the home by clinicians or caregivers include art, music, exercise, social and communication activities, and cognitive activities. These interventions are important first-line options for managing symptomology, improving functional independence and supporting well-being and quality of life [13], [14]. Over the last decade, technology-enabled interventions have been increasingly explored. Tablets or iPads have been used to set reminders, connect with friends and family to reduce loneliness [15], [16], and provide reminiscence therapy [17]. Conversational agents like "Anne" have been developed to support memory and enjoyment needs [18] and interactive robots are available for emotional support [19].

Technological support for dementia care primarily focuses on support for caregivers or persons with dementia. Technologies supporting caregivers may be more readily adopted because of greater learning abilities. However, other technologies are specifically designed for use by persons with dementia to extend memory and independence. Many of the existing dementia technologies are aimed at diagnosis by assessing images and cognitive battery scores [20], voice [21], behaviour, and function [22]. The work described in this paper is uniquely positioned to provide support for technologies that offer brain health outcome monitoring. Largely missing from the extant literature are descriptions of technologies designed to assess whether, and if, non-pharmacological interventions create meaningful change in everyday behaviours, cognition and function [23]. We focus on such assessment in this paper.

2.2. Time Series Change Detection

We assess whether healthy brain aging behaviour changes can be detected by change in smart home-detected behaviour patterns. Detecting change is typically done through supervised classification of two time series as belonging to the same category or not [24], [25], but these rely on a large number of labelled training examples. In contrast, unsupervised change detection methods compare two time series segments by estimating the ratio of probability densities for the series, known as the Kullback-Leibler divergence [26]. The two series are deemed sufficiently different if the ratio exceeds a predefined threshold.

In our earlier work [27], we designed a method to quantify change in a set of behaviour markers. The method demonstrated the ability to compare weekly behaviour to a baseline. However, the algorithm was designed to process sensor data collected by an Apple watch. In this paper, we describe how to construct a change detection method that detects and describes changes in digital markers extracted from continuous smart home sensor data.

3. Methods

3.1 Study design

The work described in this paper is part of a larger clinician-in-the-loop (CIL) study [28]. In the CIL study, ambient sensors were installed in the homes of participants age 65+ who were managing multiple chronic health conditions. The objective of the CIL study was to explore how these smart homes could be used to detect critical changes in health. Every week of the study, trained nurse researchers met with participants to update the person's health status and obtain an account of health events that occurred that week. These notes were used to validate detected changes in health status and train machine learning algorithms.

Participants could further elect to enroll in a healthy brain aging program, a modification of B-Fit [29]. The program was delivered in a flexible, individualized format to elicit and promote sustainable change in behaviour patterns. The analysis in this paper focuses on participants living alone who completed the 6-week program. The final sample included n=14 adults (age mean=84.64, std=4.85; 3 male 11 female; years of education mean=16.71, std=3.29).

Over the course of six weeks, participants met with a clinician educator (i.e., advanced clinical psychology doctoral student) once weekly for 90-minute lessons. Participants were provided with a bound booklet that contained all educational educational material that could be covered throughout the program. In session 1, participants were provided with general information about the brain, cognitive aging, successful goal setting guidelines, and healthy brain aging behaviours. In the the subsequent five sessions, participants selected a healthy brain aging topic: cognitive engagement, physical activity and and cardiovascular health, nutrition, stress, sleep, social engagement, and compensatory strategy use. Following presentation presentation and discussion of the chosen topic, the clinician educator guided the participant through a collaborative goal goal setting process that emphasized manageable, intrinsically motivating goals (e.g., increase fruit intake, walk 10 minutes each day) that could be integrated into the participant's everyday routine behaviour. As the modified B-Fit program was individualized and participant-led, participants could choose each week whether or not they wished to add an additional goal based on a new topic or continue to work on the prior week topic area. Participants were provided with standardized tracking sheets on which they rated their daily progress towards each goal: 0 = did not meet goal, 1 = partially met goal, 2 = met goal, 3 = exceeded goal. Each week, clinician educators collected the participants' self-rated goal completion scores and helped participants engage in goal problem-solving as needed.

3.2 Smart Home Data Collection

Each participant's home was transformed into a smart home by installing a CASAS SHiB (see Fig. 1). Smart home sensors included passive infrared motion detectors and magnetic door sensors. Motion detectors were placed in each functional area of the home, 2-3 sensors per room. Magnetic sensors were positioned on external doors. The number of sensors in the homes ranged from 12 to 25 (mean=17.29, std=3.58).

The sensors are discrete event. Motion sensors generate a reading when new motion is sensed in the corresponding region of the home, and magnetic sensors generate a reading when the door is opened or closed. From these readings, digital behaviour markers are extracted. These include time spent (in seconds) for each sensor-defined region of the home, aggregated by hour and day. Additional markers are constructed that represent the number of transitions that occur between regions by hour and day.

Fig. 1: CASAS motion sensors are placed on walls and ceilings; door sensors are placed on cabinets and exterior doors.

3.2 Behaviour Change Detection

To tackle the challenge of quantifying and describing changes in behaviour patterns, we utilize our Behaviour Change Detection (BCD) algorithm. BCD analyses multivariate time series data across two time periods. Let X represent a multivariate time series. Data samples are segmented into daily intervals, D, which are decomposed into equal-sized (hourly) time intervals. Information in each interval is expressed by extracted features, $D=\{d_1,d_2,..,d_{24}\}$. We compare two windows, W_i and W_j, of data within time series X, each one week long. We compute a change score, C, between the windows using a symmetric version of the Kullback-Leibler (KL) divergence measure, shown in Equation 1. C computes the total distance between the pair of distributions across the set of a digital markers.

$$C = KL_{symmetric} = \sum_{k=1}^{a} d_{i,k} \cdot log\frac{d_{i,k}}{d_{j,k}} + \sum_{k=1}^{a} d_{j,k} \cdot log\frac{d_{j,k}}{d_{i,k}} \tag{1}$$

In our analysis, we separate baseline weeks from intervention weeks. The baseline weeks represent the four weeks leading up to the start of the intervention, $\{B_1, B_2, B_3, B_4\}$. The intervention starts week 5 of the analysis and continues for the length of the participant's involvement in the study, $\{I_1, I_2, .., I_m\}$. In this study, the maximum value of m was 6 (weeks). We hypothesize that the change from B_1 to I_m will be larger than the change from B_1 to any other baseline week, B_k.

In addition to quantifying change for the population, we will look at the nature of the change that is detected for individuals in the study sample. BCD quantifies the amount of behaviour change between two weeks, but we also need a way to describe the nature of the change. For this task, we train a decision tree to act as a "virtual classifier" when comparing weeks W_i and W_j. In this method, data from W_i are labelled "negative" and data from W_j are labelled "positive". A decision tree yields a human-interpretable tree of classification rules, which we can then use to analyze the most distinctive changes that occurred.

We train a virtual classifier to describe change for the individual with the largest amount of change from baseline to end of the B-Fit program. This will help us understand the types of change that occur. In some cases, change may be related to the program and in others, change may be due to external events. We are interested in determining if the smart home can detect changes that are due specifically to new healthy behaviour adoption. To detect this, we will examine two individuals who self-reported high goal adherence values. We will focus the analysis on smart home data related to areas of the home where the target behaviour occurs. Next, we will train virtual classifiers to describe the difference in behaviour between baseline and the time when the target behaviour was initiated. We postulate that location-specific behaviours in particular will be detected by the smart home and described with the virtual classifier.

4. Results

4.1 Aggregated Weekly Change

Fig. 2 graphs the aggregated change scores, accumulated over 14 participants. In this graph, Week 0 indicates the first baseline week. Because the week is compared with itself, the change score is always 0.0. The remaining weeks indicate the change score of each week in comparison with the first baseline week. The yellow dashed vertical line separates the baseline weeks from the B-Fit program weeks. No goal was introduced the first week of the program. Across the remaining 5 weeks, participants integrated between 1-3 new goals into their routine. Finally, we fit a line to the points that include the last baseline week (immediately before the program initiation week) to the last program week.

The results show that there is increasing change through the analysed data collection period. The amount of aggregated change ranges from .308 (week 2) to .453 (week 9). Fitting a line to the values starting the first week yields a positive slope of .027. The line starting week three (the last baseline week) yields a positive slope of .008.

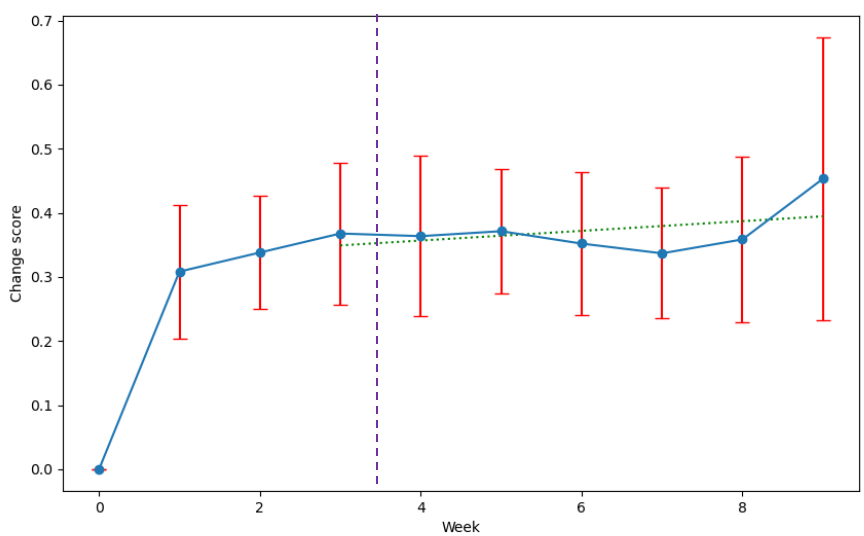

Fig. 2: Change scores for four baseline weeks and six B-Fit program weeks. Values are aggregated over 14 participants and are shown with corresponding confidence intervals. The vertical purple dashed line separates baseline from program weeks. No goal is introduced during the first week of the program. The green dotted line reflects the linear fit of change scores from the last baseline week to the last week of the healthy brain behaviour program.

4.2 Analysis of Largest Change

While Fig. 2 supports the presence of overall change during the brain health program, the large confidence intervals indicates that the actual amount of change varies between participants. Additionally, this indicates the change is not necessarily due solely to the participant initiating and sustaining the selected healthy brain activities. To better understand understand the nature of these changes, we use a virtual classifier to analyse changes in behaviour patterns for three participants.

We first look at behaviour changes for the participant that demonstrated the largest amount of change over the data analysis period. The slope of the fitted line for this participant was .054, a 100% increase from slope that was observed for the aggregated data. For this in-depth analysis, we examine the clinical notes for the participant during the corresponding time interval. Additionally, we train a virtual classifier to distinguish behaviour patterns between the baseline weeks and the brain health program weeks. Fig. 3 shows the virtual classifier for this participant.

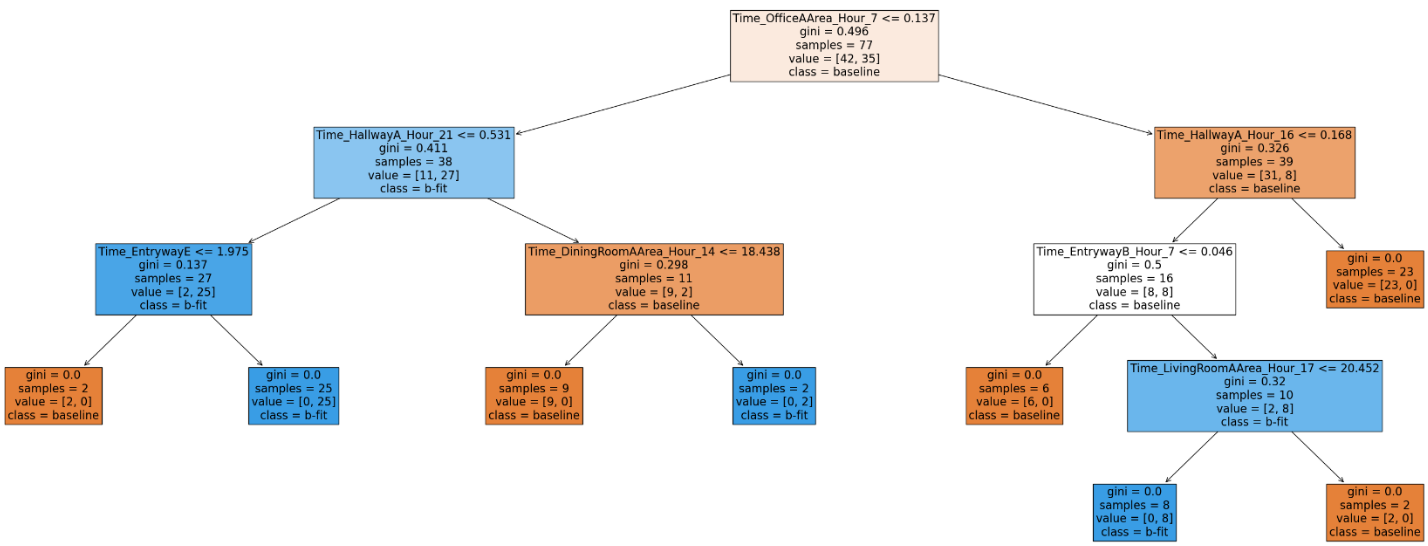

Fig. 3: Learned decision tree distinguishing class "baseline" (smart home-based behaviour markers collected during baseline weeks) from B-Fit (markers collected during B-Fit healthy behaviour program weeks). Left branches are followed when the tested condition is true. In the decision trees, "gini" indicates the gini impurity at that node.

This participant selected new behaviours of increased outdoor walking, eating more fruits and vegetables, and focusing on the cognitive task of knitting. At first glance, the virtual classifier decision tree yields surprising results given the participant's selected healthy behaviours. The tree shows that during the program weeks, less time was spent in the kitchen, more time was spent in the hallway, and more time was spent in the living room. Notes from the nurse research team shed light on these changes. During the program weeks, outside physical activity was paused due to the participant's heart condition. Instead, the participant focused on walking in the hallway area for their physical activity goal. The participant used the living room recliner to knit, consistent with spending more time at that location to meet a cognitive activity goal.

4.3 Analysis of Goal-Adherent Participants

Finally, we look at specific changes in behaviour for two participants who self-reported that they consistently met or exceeded their weekly behaviour goals. The first case, shown in Fig. 4, was a participant who committed to work on puzzles each day at the table for cognitive stimulation, in addition to other goals that were performed outside the home. Focusing solely on behaviour at the table, we see from the tree that the person spent more time there during the B-Fit weeks than during baseline.

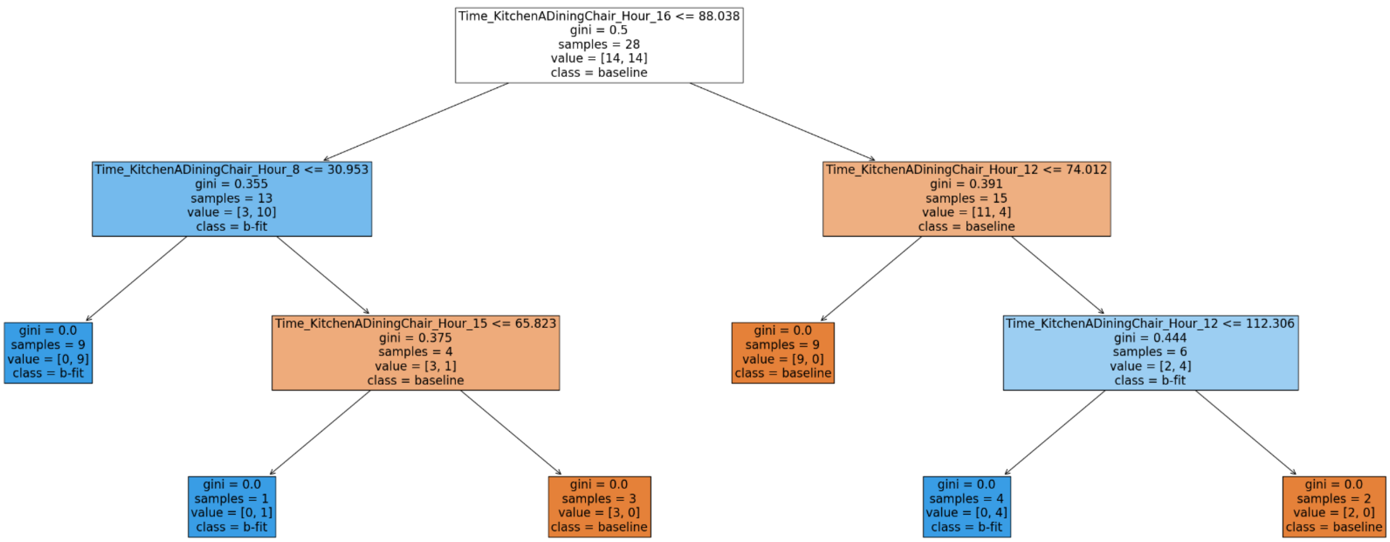

Fig. 4. Decision tree reflecting behaviour consistent with increased time working on puzzles at the dining table.

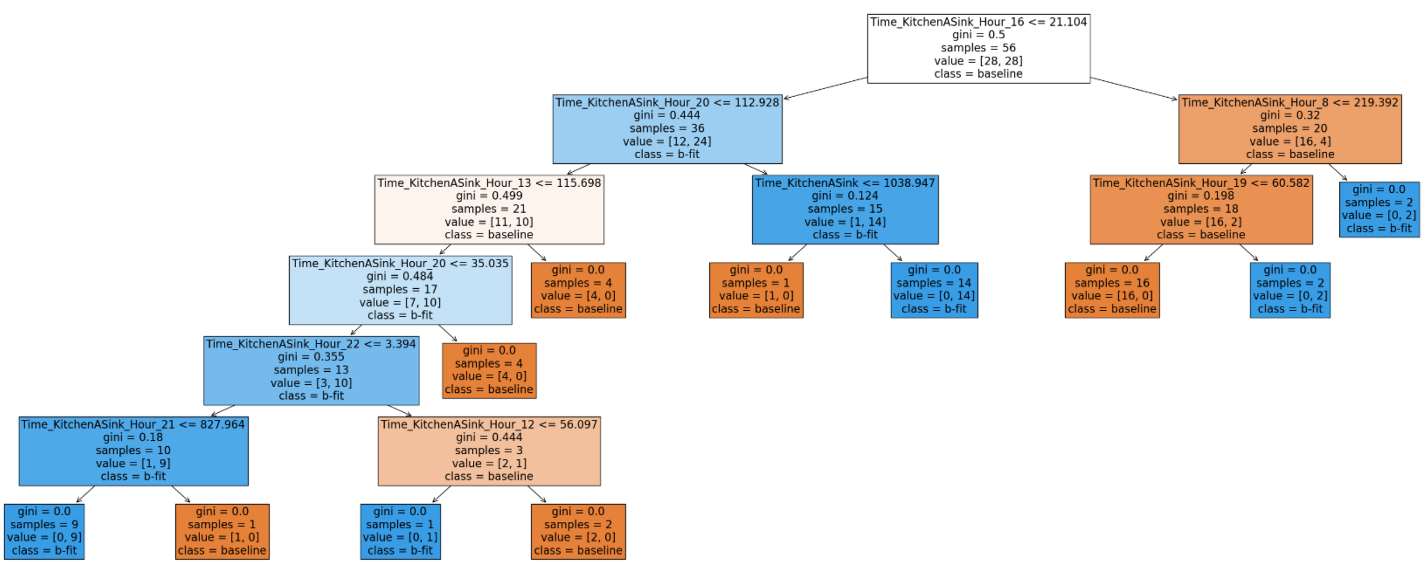

Fig. 5. Decision tree reflecting more time at the kitchen sink obtaining water to drink and prepping fresh food.

In the second case, we look at behaviour change for a participant who reported high adherence to the goals of drinking more water at the hours of 1000, 1600, and 2000. This person stated that their daily intake did increase and was sustained throughout the B-Fit program. The decision tree in Fig. 5 focuses on time spent at the kitchen sink during baseline and B-Fit weeks. We see that time during the 1600 and 2000 hours were top node discriminators with half of the B-Fit samples having greater overall time at the kitchen sink and time during 2000 during the B-Fit program.

5. Discussion and Conclusion

In this study, we examine the ability of smart home and machine learning technology to monitor everyday behaviour and detect changes that occur during a healthy brain behaviour change program. We offer a behaviour change detection algorithm that quantifies the change in digital behaviour markers between two windows of time, then use a decision tree virtual classifier to examine the types of differences that occur.

Overall, the B-Fit weeks did correspond to larger changes in behaviour than occurred between the four baseline weeks. Examining the nature of the changes, we observed that some of the changes were due to external factors and health events, rather than planned changes in behaviour routines. These observations highlight an additional benefit of monitoring behaviour with smart home sensors and examining changes in digital markers. The largest changes accompanied health difficulties encountered by a participant. Detecting these changes may play an important role in early detection of health events and more effective treatment. For individuals who did stick to their selected goals, the changes in behaviour supported the planned incorporation of new behaviours, including completing puzzles, knitting, and drinking water.

The study did face several limitations. Changes in behaviour may occur due to many factors, including visitors, holidays, and external events, in addition to changes in health and incorporation of new healthy behaviours. Additional work is needed to be able to identify and understand all influences on these changes from sensor data alone. Additionally, some of the selected behaviours, such as a stress management goal related to positive affirmations, could not be detected by the sensors while others were not performed within the home. For example, some participants elected to walk outdoor or go to a community library. Future work may consider use of wearable sensors to obtain more complete information on behaviour routines and analyse behaviour changes that result from interventions.

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