Intelligent Data Processing to Support Self-Management and Responsive Care in a Smart Home Environment

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Declaration

"This study was completed for Doctorate in Philosophy at the University of West of England. The work is my own. Where the work of others is used or drawn on it is attributed"

Acknowledgements

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I am very grateful to all the care workers who participated in my interviews and helped focus my research. These interviews form a key part of this thesis without which this work would not connect to real-world applications. I would also like to thank all the participants who participated in my meal preparation data collection which was a core element of this study that allowed the technical development to take place.

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Abstract

This research is situated in the area of ambient intelligent systems for assisted living. The motivation for the research was to understand how ambient intelligent systems could be used to support people with learning disabilities in providing more personalised care, as well as function as an aid to support independent living. In the first phase of the research a series of interviews conducted with formal carers of people with learning disabilities highlighted kitchen activities as a potential area of support. This provided a focal point for the research whereby subsequent research involved the development of sensor data mining techniques and machine learning methods to recognise specific meal-preparation activities with a view to supporting task prompting. The goal of task prompting is to enable automated intervention for service users performing meal-preparation activities by tracking the activity in real-time by analysing ambient sensor data. In the second phase of the research a public smart-home dataset was used to develop a novel methodology which uses "temporal clusters" of sensor events as a pre-processing step for extracting features from the data and creating visualisations. In the third phase of the research, a data set comprising different meal-preparation activities undertaken by three participants in a shared kitchen was collected over a period of 8 weeks. This fully annotated dataset includes a combination of data from a range of ambient smart-home sensors and low-resolution thermal cameras. This dataset was used to experiment with knowledge-driven activity recognition techniques, which were used to develop a novel hybrid offline-online learning methodology for real-time activity recognition and prediction. This methodology is shown to overcome the shortcomings of existing supervised activity recognition methods, which require re-training with new data if the activity changes. The new methodology has been designed to enable learning from the user in order to track meal-preparation activities in real-time, detect deviations from the activity, and adapt to changes in the user's performance without requiring re-training. The research presented in this thesis, together with the meal-preparation dataset, are a crucial stepping-stone for the development of future technologies that offer the potential for real-time task prompting and thus could be useful in supporting people with learning disabilities in performing activities more independently. The approaches developed can also generate information that could help carers better understand how their service users are able to perform these activities and hence personalise and adapt the support they provide.

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List of Acronyms

A

AAL Ambient Assisted Living.

ADL Activities of Daily Living.

B

BPNN Back Propogation Neural Network.

BSN Body Sensor Networks.

C

CASAS Washington State University's Center of Advanced Studies In Adaptive System.

D

DFLAR Device-Free Wireless Localisation and Activity Recognition.

H

HAR Human Activity Recognition.

I

IoT Internet of Things.

L

LD Learning Disabilities.

P

PIR Passive Infrared.

R

RL Reinforcement Learning.

S

SH Smart Home.

SVM Support Vector Machine.

T

TD Temporal Difference.

W

WSN Wireless Sensor Networks.

Chapter 1

Introduction

Over recent years, Smart Home (SH) and the Internet of Things (IoT) devices have become increasingly popular, with their global installed base growing by over 161 million units between 2010 and 2016 (IHS Markit 2016). In the mid-2000s, research into ambient and pervasive computing had started progressing rapidly which lead to the integration of everyday items and home appliances with various sensors, actuators and relays, along with their inter-networking to perform various forms of automation and data analysis (Demiris & Hensel 2008). A decade later, these products have become much more standardized, cost-effective, and readily available. This has created an ongoing imperative to explore how technology like SH sensing devices can be used to support people in their own homes (Chen et al. 2020).

As the number of vulnerable people grows, the care industry is put under increasing pressure to balance high quality care with reduced budgets (Kvedar et al. 2014). This leads to reduced 1-on-1 time between the service user and their care provider who can also often be the only social contact the service user has. This has spawned various tele-monitoring and care companies in recent years (Siegel & Dorner 2017), which utilise IoT technology to provide monitoring solutions which could help care providers take more action remotely or over the phone when they are unable to visit. This monitoring however, has been limited to simple movement sensors or contact sensors on doors being triggered, which sends out an alert to the relevant person. Although this is still beneficial, there is much more utility which can be provided by these IoT devices. This is further made evident by the growing movement of industry 4.0, combined with the number of cloud-based IoT analytics platforms such as Microsoft Azure, Google IoT Core, and Amazon Web Services IoT Analytics, which utilise machine learning and data analytics for IoT devices (Muhammed & Ucuz 2020). Such solutions are actively being used in other industries to reduce workload on staff, while they still remain to be utilised by the care providers. As will be discussed further in this thesis, the care industry and their users pose unique challenges which need to be addressed before the full potential of IoT technology can be utilised for healthcare providers and their service users. These challenges range from the social model of acceptability and privacy, to more technical challenges in the use of machine learning and data processing techniques. While this PhD briefly investigates the former in order to direct the research towards solutions which are practical, the major focus and subsequent contribution of this work is in investigating the latter.

Accordingly, the goal of this PhD is to investigate and develop intelligent data processing techniques for SH sensor data to support people with long-term conditions in order to live more independently. These sensor data processing techniques form the core of this thesis with a major focus on tracking activities in real-time as well as extracting actionable information from the data which would in-turn enable the person to live more independently and allow care providers to be more responsive.

The next subsection further explains the background and the motivation behind the research, before delving into the main aim and consequent research questions.

1.1 Background and Motivation

Over the past decade, researchers have investigated the use of SH and IoT devices to support independent living, which has led to the development of various concepts and new terminology. These concepts and terminology are crucial to understanding the challenges which present themselves for the deployment of IoT based intelligent solutions in the assisted living domain.

Accordingly, this section will first detail the technology and associated concepts which form the domain of *Ambient Assisted Living*, which is the domain that this PhD research is situated in. Following which, the concepts of *Human Activity Recognition* and associated sensors are discussed. Here, various different sensors along with their advantages and shortcomings are also briefly discussed. And lastly, this section will explain the use of various machine learning techniques which are utilised for extracting useful information from sensor data for the purpose of performing Human Activity Recognition. This breakdown of the various domains is presented in the form of a Euler diagram in figure 1.1.

The goal of this section is to demonstrate the need for certain types of machine learning techniques to be the focus of future development in order to make intelligent IoT based solutions practical for Assisted Living, and therefore, set the scene for the main aim and research questions that follow in the next section.

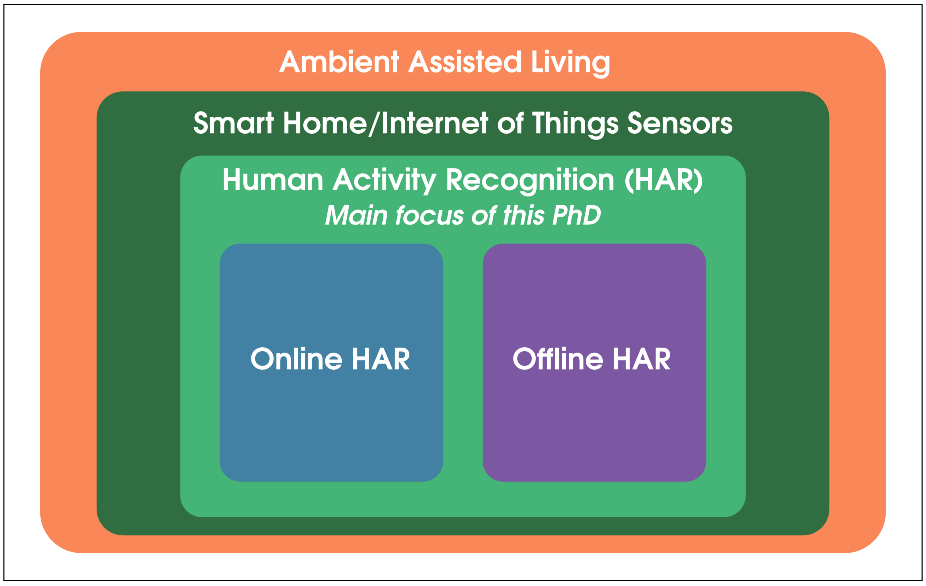

Figure 1.1: Euler diagram showing the relevant domains of Ambient Assisted Living

1.1.1 What is Ambient Assisted Living?

According to a report by He et al. (2016) an estimated 8.5% of the world's population (617.1 million) is aged 65 or above. This number is projected to increase by over 60% by 2030, when there will be 1.6 billion older people worldwide. It is estimated that 89% of older adults prefer to stay in the comfort of their own homes, where nursing home care costs can rise rapidly (Rashidi & Mihailidis 2013). To address this, researchers have been investigating the development of Assisted Living technology which aims to not only help people live longer, but also live healthier. This includes the development of products that would assist its occupant in Activities of Daily Living (ADL) such as cooking, cleaning, bathing, etc. as well as provide support to the carer. Products developed in the field of Assisted Living can range from assistive robots, mobile manipulators, tele-operated robots to wearable technologies (Deegan et al. 2008).

Ambient intelligence is a field of technology that aims to make the environment responsive and adaptable through the use of sensor data, pervasive computing and artificial intelligence (Cook et al. 2009). This has led to the development of a range of SH sensors and devices. In recent years, researchers have attempted to integrate Ambient Intelligence with Assisted Living systems to form Ambient Assisted Living (AAL). AAL technology aims to utilise data from SH sensors and devices embedded in the users' environment combining it with assisted living technology (such as assistive robots) to support people with long-term conditions to live independently (Kvedar et al. 2014). This can include supporting older people with cognitive impairments, people with learning disabilities, and people with acquired brain injuries. In order to achieve this, SH systems often need to make intelligent decisions based on the user's activity using advanced data processing techniques. This data processing forms the core of this study.

1.1.2 Offline and Online Human Activity Recognition using Smart-Home Sensors

In the field of AAL, data processing is often used for three main purposes – Human Activity Recognition (HAR), intent prediction, and data evaluation/reporting (Rafferty et al. 2017). Out of these three, HAR remains the largest area of research. This includes offline HAR aimed at detecting and/or categorising activities after they have finished, and online HAR aimed at detecting activities in real-time as they occur, as well as tracking the activity step-by-step. Online HAR is essential for interventions such as assistive prompts, while offline HAR is useful for tracking changes in user behaviour over time, detecting abnormal behaviour, as well as performing wellness evaluations. HAR can be performed for simple activities such as sitting, lying down, walking, etc. as well as complex activities such as meal preparation, meal consumption, and so on. For the purpose of this study, HAR will mainly refer to recognising complex activities.

The sensors traditionally used for HAR can be broadly categorised into ambient Wireless Sensor Networks (WSN), Body Sensor Networks (BSN), and video-based solutions. Ambient WSN comprise of sensors that are integrated into the environment of the user such as Passive Infrared (PIR) motion sensors, magnetic contact sensors, and temperature sensors. These are often battery-operated sensors which can be retrofitted in an existing house, and have a relatively long battery-life of up to two years. Generally, a large number of WSN are required to be present in order to perform HAR (Cardinaux et al. 2011). BSN are comprised of sensors which can be physically present on the user, such as wearables, and can provide accelerometer data, GPS data, as well as information on the user's physiological condition. The data provided by BSN is much more in-depth when compared to ambient WSN, however, BSN are considered more intrusive and the end-users can often forget to wear the sensors or charge them. Video and audio based solutions provide the most context on the user, however end-users often see them as an invasion of their privacy. These solutions are also much more resource intensive in terms of computing requirements (Boise et al. 2013, Liu et al. 2016). As cost-effective ambient WSN are becoming more commercially available and are considered more acceptable than video-based solutions, exploring and developing their utility as part of an effective HAR technology solution to support users for living independently is a crucial next step. There are also other types of sensing techniques which do not fit into the traditional categories, such as device free wireless localisation and thermal imaging. A more in-depth review of current HAR techniques and associated sensors is presented in the literature review in chapter 2.

1.1.3 Supervised Learning Methods for Performing Human Activity Recognition

In addition to offline and online, HAR can also be categorised based on the underlying machine learning techniques utilised as supervised or unsupervised. Traditionally, there has been a lot of focus on using supervised methods for HAR which include machine learning techniques that are trained on a large set of labelled data, following which they are able to assign labels to new and previously unseen data points. In terms of HAR, this means training the system on large amounts of labelled sensor data, where the label describes the activity (such as Meal_Preparation). When the system processes any new data, it is then able to categorise it accordingly. The accuracy of these systems depends on various factors, such as the quality of the training data itself as well as the model of the supervised system, however, in existing works supervised systems have shown to have accuracy up to 99% for categorising human activities (Uddin & Torresen 2018).

1.1.3.1 Shortcomings of Supervised Learning Methods

Even though supervised techniques have generated promising results in previous studies, they also have certain shortcomings. A significant issue with supervised systems is the collection of labelled data. A common approach when collecting data for training classifiers requires the user to self-report or log activities through a diary, which is then used to annotate the data (van Kasteren et al. 2008). This introduces issues related to the reliability of the labels, as the user may forget to label every activity he/she performs or may not provide sufficient detail describing the activity. This is evident in many user-annotated public SH datasets where the aforementioned "Meal_Preparation" label is provided that can encompass a range of different types of cooking activities. Self-reporting of activities can be a tiring and tedious task, particularly when required to be conducted over many weeks or months and may not be possible for end-users with cognitive impairments. Secondly, it is important to note that the system will not recognise any new activity which was not included in the original training data, in fact if the Meal_Preparation activity changes significantly over time, the system at some point will stop recognising it. Essentially, all this means is that for mass deployment the system would have to be trained for each user separately for it to work, and if the user's habits change significantly over time, the system will need to be retrained with more labelled data. These challenges make supervised HAR less practical for mass deployment and less cost effective, as data collection and labelling is a costly undertaking. In conclusion, it can be said that supervised HAR works well in theory, but leaves a lot to be desired in practice for real-world large scale deployment.

1.1.4 The Case for Unsupervised and Semi-Supervised Learning Methods

Due to the various issues regarding the practicality of supervised HAR systems listed previously, researchers are also investigating the use of semi-supervised and unsupervised learning techniques, with a view of eliminating the need for labelling SH data. Unsupervised machine learning include the use of various techniques which are able to segment or categorise data without the need for training through labelled data. A common sub-domain of unsupervised machine learning techniques includes clustering algorithms that sort the data points into different clusters based on the data point's differences/similarities. Additionally, certain unsupervised machine learning algorithms are designed to automatically categorise any new or unseen data by forming a new cluster. This makes unsupervised HAR techniques much more adaptable and personalisable when compared to traditional supervised HAR techniques. However, most of the existing research studies that have shown promising results through unsupervised methods used context-rich information obtained from BSN and video-based solutions, and not ambient WSN.

There is also a third category of machine learning techniques, known as semi-supervised learning. These are either supervised or unsupervised algorithms which are implemented in such a way as to require some form of supervision to work, which can be in the form of a small set of labelled data or through feedback from user interaction. Existing research into semi-supervised HAR methods suffer from the same issue as unsupervised HAR, they generally require context rich information only provided through BSN or video based solutions (Saunders et al. 2016, Chen et al. 2020).

Therefore, the further development of unsupervised and semi-supervised HAR to work without the need of video cameras or BSN could be the key to making intelligent AAL technology practical enough for large scale deployment. This creates the potential for combining offline HAR with online HAR in order for the system to learn to recognise user activities by evaluating past activity sessions offline first. The SH ecosystem utilising a hybrid offline-online HAR approach is proposed in figure 1.2.

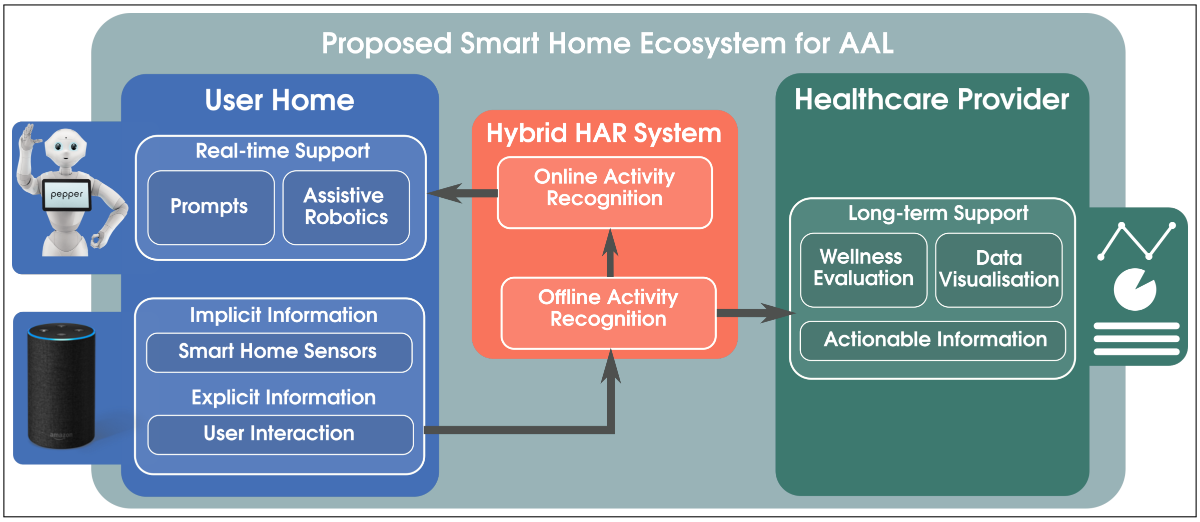

Figure 1.2: Proposed Smart Home Ecosystem for AAL with a hybrid offline/online HAR system

The hybrid HAR system receives implicit and explicit information from the user's home and processes both, long-term sensor data for offline HAR as well as real-time sensor data for online HAR. The online HAR system then connects to devices in the user's home to provide real-time support in the form of automated prompts and assistive robotics. While the offline HAR system extracts useful information from past activities to support the online HAR, as well as provide actionable information to the care provider through wellness evaluations and data visualisations. With this in mind, the next section outlines the main aim and research questions of this study.

1.2 Main Aim, Research Questions and Methodology

This section presents the main aim, research questions, and the overall methodology of this study. These build upon the background and motivation presented in the previous section, particularly the need for semi-supervised and unsupervised HAR techniques. Each subsequent chapter in this thesis further expands on the methodology presented here, detailing the procedures followed to conduct the research covered in that chapter.

It should be stated that in order to focus the research to a more specific target user group, and based on the availability of healthcare providers for participating in the user engagement study during the PhD timeline, people with Learning Disabilities (LD) and their care providers are identified as the target user group for this research. Furthermore, a literature review revealed that existing research investigating AAL technology focus on other vulnerable groups such as older people with LD, and research that includes people with LD often group their requirements with other vulnerable groups. Therefore, this provides an opportunity to investigate the user requirements and undertake technological development specifically for supporting people with LD.

Accordingly, the overarching research question of this study is to investigate: **How can SH technology be used to support people with LD to live more independently and receive more responsive care?** To address this question, we have articulated the following research questions which fit into two themes: user needs and requirements, and technological solutions. Referring to figure 1.2, the first theme helps us identify support requirements and suitable sensors, while the second theme helps develop the HAR techniques.

1.2.1 User Needs and Requirements

The purpose of the research questions presented in this theme is to gain an understanding into the support needs and requirements of people with LD in the context of AAL systems. This includes understanding which care requirements being fulfilled today can be potentially supported through SH sensing technology. This also helps identify a set of specifications that the technological solutions must meet, and therefore would be used to evaluate the results of the technical work conducted in this PhD. Accordingly, the first research question is:

RQ1. What type of support is needed by people with LD in order to live more independently in the context of Ambient Assisted Living?

Answering this research question helps identify the areas of support needed by the service users in order to perform their everyday tasks, specifically focusing on support areas which can be augmented by SH sensing technology. This includes understanding which activities carried out by the service users are of interest to their carers and what shortcomings in the support provision currently exist that can be augmented by SH technology. This research question is then further articulated through the following research objectives:

Research Objective 1.1: Conduct literature review to investigate independent living requirements of people with LD in the context of AAL systems. This includes identifying shortcomings in the care provision service which can be supported by the use of SH sensing technology.

Research Objective 1.2: Perform primary research by engaging with care providers to further verify findings from Research Objective 1.1 as well as identify any new areas of support that can be addressed by the research conducted in this PhD.

RQ2. How could SH sensing technology be best utilised to augment the support provided by care providers?

Once support areas which can be supported through SH sensing technology have been identified, the next step is to identify how SH sensing technology could augment that support. This includes identifying the type of SH sensors to be used in the study along with barriers to the technology and other limitations due to factors such as the environment of the service user, privacy concerns, and user acceptability. This research question can be further articulated through the following objectives:

Research Objective 2.1: Conduct literature review to investigate proposed technological solutions that use SH technology for supporting people with LD as well as people with other long-term conditions. This objective is an extension to objective 1.1, bringing the focus to reviewing existing technology, and is done to identify any limitations of the existing solutions in the context of RQ1, which need to be addressed by research conducted in this PhD.

Research Objective 2.2: Perform primary research by engaging with care providers to further verify findings from Research Objective 2.1 as well as identifying new applications, use-cases, and restrictions in the use of SH sensing technology for supporting people with LD.

The main finding of both these research questions (expanded upon in Chapter 3) are that there are in fact two user groups: people with LD and their care providers. Therefore, in order to support people with LD in living more independently, the technological solutions need to support both the person with LD as well as their care provider. It was identified that the service users require in-house and real-time support for performing activities, while the care providers require sensing technologies for providing actionable information. The research questions also helped identify meal preparation activities as the primary focus of this research, as it is a key activity that most service users need support and prompting with, and tracking activity in the kitchen can also help provide a snapshot of the service users' daily routines. These findings then helped articulate the second theme of this research: technological solutions.

1.2.2 Technological Solutions

The research questions presented in this theme build upon the findings of the previous research questions. Accordingly, there are two research questions to focus on the two user groups, with meal preparation activity being the centre focus of the technological solutions.

RQ3. How can SH sensor data be utilised for informing care providers about changes to the service user's kitchen activities?

Through RQ1 and RQ2, it was identified that tracking activity in the kitchen to provide actionable information to care providers is key for enabling responsive care. Therefore, the first research question focuses on the viability of tracking changes in kitchen activity from the SH sensor data. Answering this question involves the investigation and development of offline HAR techniques for utilising historical SH sensor data in order to provide the information needed by the care providers as identified in RQ1 and RQ2. This would enable care providers to track changes in the service users' kitchen activities and adjust their support accordingly. This research question is further articulated through the following objective:

Research Objective 3.1: Utilise smart-home sensor data for extracting information that can be used to identify changes in a person's kitchen activities over time.

Following this, we then investigate how support can be provided to the service-users directly. For service users, RQ1 and RQ2 helped identify self-management of kitchen activities as being crucial to enable more independent living. Therefore, the utility of SH technology to enable real-time support must be investigated.

Accordingly, the fourth research question is:

RQ4. How can real-time support for meal preparation activities be enabled by the use of SH technology?

The key to enabling real-time support for meal preparation activities is to be able to track the activities step-by-step in real-time. This in-turn could be utilised to enable interventive solutions through assistive robotics or automated prompting. Therefore, the goal of the technical development for this research question is specifically on tracking meal preparation activities step-by-step through the use of SH technology. Accordingly, answering this research question will include developing online HAR techniques in order to stream SH sensor data and track the service user's activity in real-time. The goal of this real-time tracking is to enable the system to predict the next most likely action to be taken by the user during the activity, as well as detect points in the activity where the service user deviates from their usual process and would therefore require intervention(s). This research question is further articulated through the following objectives:

Research Objective 4.1: Collect real-world data of meal preparation activities utilising SH sensors identified in RQ2.

The data would include preparation of different types of meals by various participants. This data collection is essential because most public datasets which have recorded data from the real-world only include generic data labels for activities such as meal preparation, making it impossible to verify results from HAR techniques aimed to distinguish between different types of meal preparation activities as well as track the activity step-by-step. Which leads us to the second and third objectives that utilise offline and online HAR:

Research Objective 4.2: Utilise the collected meal preparation dataset to develop offline HAR techniques for automatically extracting essential information/features from the sensor data.

Research Objective 4.3: Use the information extracted through offline HAR to perform online HAR in order to track the meal preparation activity in real-time, and demonstrate how this can be utilised for identifying deviations in the activity.

The novelty of this technical development, which removes the need for labelled data, lies in the development of a hybrid offline/online activity recognition approach that utilises offline activity recognition to model activities from unlabelled sensor data and combines it with online streaming sensor data to identify changes in the modelled activities and evolve its knowledge base accordingly. This enables the system to learn from the user with every new session incrementally without requiring expertly labelled data. This hybrid HAR approach broadly consists of three stages – building user activity models, tracking that activity over the long-term, and detecting when the activity is taking place in real-time in order to provide support/interventions and evolve its knowledge base. Additionally, the technical development in this PhD is focused on semi-supervised machine learning techniques which can essentially learn from the user, due to reasons listed in section 1.1.4 and expanded upon in the literature review. Semi-supervised here refers to machine learning techniques which analyse a large set of unlabelled data while utilising a small set of labelled data obtained through user interaction. This user interaction refers to the system's interaction with the carers as well as the service users, depending on the cognitive capabilities of the service user. The overall journey of this research is shown in 1.3.

The research is conducted through a combination of qualitative and quantitative methods. The qualitative research involves an exploratory thematic analysis of interviews conducted with care providers to answer RQ1 and RQ2. It also involves evaluating data visualisations for RQ3 generated from HAR techniques used on a public SH dataset to meet the requirements established from the interviews. The quantitative research in this PhD involves testing HAR techniques against the ground truth from both a public SH dataset (where possible) as well as data collected during the PhD.

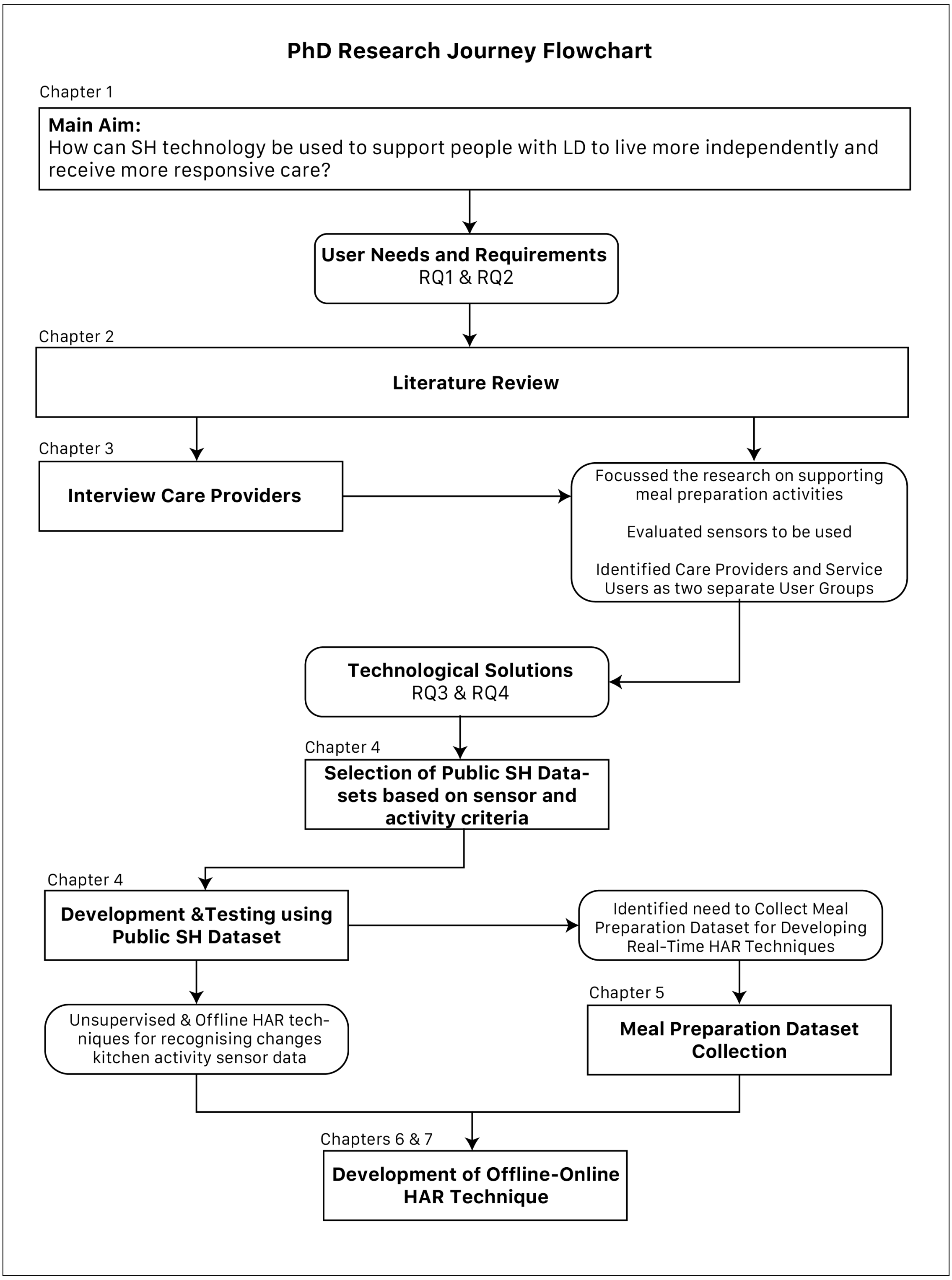

Figure 1.3: Flowchart showing the research journey of this PhD

Following description of the main aim and research questions of this PhD, the next sub-section defines the scope of this research in more detail.

1.2.3 Scope of the research

The architecture shown in figure 1.2 has several variables and each of them would require extensive investigations unless the scope of the research is defined. From figure 1.2, the core of this PhD is focused on the hybrid HAR system. However, in order to develop such a system, requirements and limitations of the user and their home as well as the care provider also need to be investigated. As explained in the research questions, it is important to establish which user activities can benefit from such an AAL ecosystem as well as identify which types of sensors and SH devices would be acceptable to the user. Accordingly, the following points list the assumptions which have been made to help further define the scope of this research:

- As this research investigates semi-supervised techniques, it is assumed in later chapters of this thesis that certain information from the user is available to the system. One such crucial information is the identity of the person performing the activity. This is important as people with LD often live in shared environments, so the HAR system needs to be able to distinguish between the different residents. The actual user interaction technologies for this are out of scope, however, recommendations for investigating specific technologies for this are made wherever relevant.
- Similarly, the resulting intervention techniques arising from the hybrid HAR approach presented in figure 1.2 is a large area of research by itself. Therefore, the focus of this study is on the hybrid HAR approach and while certain intervention/data visualisation techniques based on the hybrid HAR are presented in this thesis, further rigorous investigation into the effectiveness of such interventions needs to be conducted in the future.
- To focus the technical work carried out in the later chapters of this thesis, it is assumed that only the person performing the meal preparation activity is present in the kitchen. It must be noted that in a real-world scenario, there may be other individuals present in the kitchen during the activity which could increase the noise in the sensor data. Recommendations have been made as to how this could be countered, however, the main research focus of the technical development assumes only a single person to be present for the activity.

The metric for evaluating the work presented in this study and the subsequent claims made are based on the accuracy of the hybrid HAR system and not the real-world effectiveness of resulting solutions. Therefore, this study does not provide an evaluation of the real-world effectiveness of the resultant HAR system on service users and data visualisation techniques for care providers. These would require a separate study with its own set of aims and research questions.

1.3 Research Contributions

By answering the research questions presented in this chapter, the following research contributions are identified:

- Establishing requirements for people with learning disabilities and their care providers.
- Development of temporal cluster extraction and visualisation techniques using a public SH dataset.
- Real-world sensor data collection of three unscripted meal preparation activities from three participants, with more detailed data labelling compared to public datasets.

- Integration of offline and online HAR techniques to form a hybrid semi-supervised HAR system, enabling real-time tracking of meal preparation activities while being able to adapt to changes over time.

In addition, the research in this PhD led to the following publications:

Gupta, P., McClatchey, R. and Caleb-Solly, P., [In Review]. Intelligent IoT Systems to Support Self-Management – Requirements for People with Learning Disabilities and their Care Providers. *In 17th International Conference on Intelligent Environments*

Gupta, P., McClatchey, R. and Caleb-Solly, P., 2020. Tracking changes in user activity from unlabelled smart home sensor data using unsupervised learning methods. *Journal of Neural Computing and Applications*, pp.1-12.

1.4 Structure of Thesis

The rest of the thesis is structured as follows:

Chapter 2 reviews the previous works that relate to this study. The chapter is divided into four sections: background on people with learning disabilities, ambient assisted living, smart home sensors, and data processing and machine learning.

Chapter 3 establishes the carer and service user support requirements which need to be addressed in this PhD. These are established through interviews conducted with care providers for people with long-term conditions.

Chapter 4 details the research conducted in this PhD for offline HAR systems using a public SH dataset. This includes the use of unsupervised machine learning techniques in order to track long-term changes in user behaviour.

Chapter 5 details the experiment design and procedure followed for the data collection and labelling conducted in this study.

Chapter 6 presents the analysis of the collected dataset along with the utilisation of offline HAR techniques for modelling user activities.

Chapter 7 further builds upon the work from Chapter 6, presenting a methodology for performing online HAR utilising the models built from offline HAR.

Chapter 8 finally provides a discussion of the research conducted, relating it to the research objectives from Chapter 1, literature review from Chapter 2, as well as identifying the limitations and the overall contribution of the work.

Chapter 2

Literature Review

As a starting point, it is crucial to review existing literature in the field to identify gaps that can be addressed through this study. It is also important to establish the current state of the art, to ensure that this study builds upon the latest developments in the field while still providing a novel contribution. It should be noted that although this PhD is focused on research for people with LD, the literature is reviewed in a broader context which includes other vulnerable groups such as older people with cognitive impairments. This is because the majority of research into AAL technology is focused on supporting the ageing population (Fan et al. 2017), but wherever possible specific literature relating to people with LD is also included in this review.

The search terms used for conducing this literature review are outlined in figure 2.1 according to the research questions. The search led to 239 studies being identified initially based on their title and abstract. These were then narrowed down to 101 studies after performing a full-text review. The resultant papers were then organised thematically into three main themes and associated sub-themes - Ambient Assisted Living which includes papers that outline AAL requirements, views on SH development, and barriers to SH adoption; Smart Home Sensors which includes papers describing sensor requirements and the types of sensors used for HAR; and Data Processing & Machine Learning which is comprised of papers focused on HAR techniques. These themes are further outlined in Figure 2.2.

This chapter is divided into sections based on the themes presented in Figure 2.2, with an additional sub-section at the end to provide a summary.

Literature Review Search Process

RQ1. What type of support is needed by people with LD in order to live more independently in the context of Ambient Assisted Livings?

RQ2. How could SH sensing technology be best utilised to augment the support provided by care providers?

Combination of Key Words Used:

Learning Disabilities	+	Assisted Living OR Smart Home OR Independent Living OR Support
Ambient Assisted Living OR Assisted Living OR Smart Home OR Human Activity Recognition	+	Requirements OR Sensor Requirements OR Barriers OR Adoption OR Challenges

RQ3. How can SH sensor data be utilised for informing care providers about changes to the service user's kitchen activities?

RQ4. How can real-time support for meal preparation activities be enabled by the use of SH technology?

Combination of Key Words Used:

Smart Home OR Assisted Living	+	Kitchen OR Meal Preparation OR Activity OR Adaptive	+	Visualisation OR Tracking OR Recognition OR Prompting

Meal Preparation OR Real-time OR Adaptive	+	Activity Recognition

239 studies screened based on title and abstract

101 studies included after assessing full-text articles

Figure 2.1: Search process of the literature review

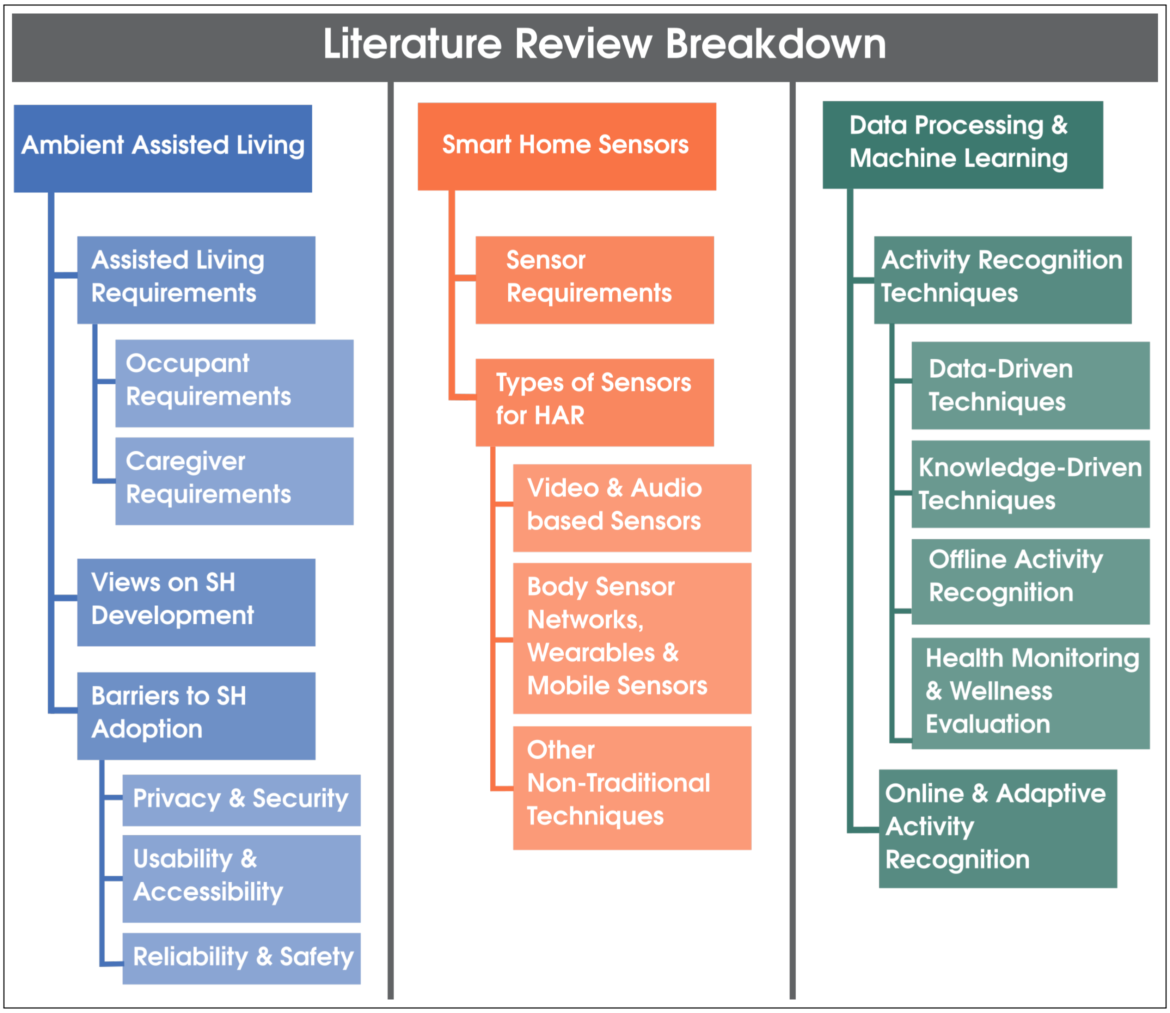

Figure 2.2: Breakdown of the literature review

2.1 Ambient Assisted Living

The following subsections review papers that provide insights into the development of AAL and SH technology. These papers are further divided into three categories - Assisted Living requirements, views on SH development, and barriers to SH adoption.

2.1.1 Assisted Living Requirements

The goal of AAL is to support both the carer and occupant, instead of just replacing the carer. To quote Heath and Bell - "the point of technology is not to replace experiences that we already enjoy today with our families... [but to] support or enhance experiences you already enjoy... but in new ways" (Heath & Bell 2006). Therefore, this area of research must be conducted carefully to augment the support provided by carers in a way which helps the user become more independent. Queirós et al. (2015) divides the target users of AAL into clients and caregivers. Clients are defined as the users living in the SH while caregivers can be formal or informal healthcare providers. Reviewing this literature gives us insight into AAL SH user requirements that could be satisfied by research conducted in this PhD. The following sections have been divided into the SH requirements of the occupants and those of the caregivers.

2.1.1.1 Occupant Requirements

Wilson et al. (2015) focus on older people with cognitive impairments and suggest the primary needs of these users as accessibility to emergency help contact, assistance with cognitive impairments, and automatic systems to detect and prevent falls. However, a point made by the authors which is relevant to other vulnerable groups highlights the importance of supporting the occupant to live independently by providing prompts and reminders instead of simply taking control away from the users. Saunders et al. (2016) emphasize the significance of co-learning and reablement in the field of AAL. They define co-learning as the process of a human user and a machine working together to achieve a particular goal, and reablement as the process of supporting the human user to do something rather than doing it for them. Research by both Saunders et al. (2016) and Wilson et al. (2015) inform this PhD as they both reinforce the utilization of prompts and reminders in a SH to guide the user through a task instead of utilizing assistive robots to perform the tasks for them.

Another less apparent requirement of a SH is the need to adapt to changing user health and lifestyle over time. This adaptability has been suggested by several papers for a SH to continually provide support to its users as their health conditions improve or deteriorate over time (Balta-Ozkan et al. 2013, Viani et al. 2013, Wilson et al. 2015). This is crucial for the SH to be personalisable and practical for the user, which is why adaptability is a major focus in this PhD.

A paper by Gagnon-Roy et al. (2020) presents findings on a smart cooking assistant named COOK in order to facilitate meal preparation for adults with severe traumatic brain injuries. The study identified benefits as well as various obstacles of implementing such technology. The obstacles included the logistics surrounding the implementation of such technology and the limitation of the solution for clients with specific profiles. It was suggested that "few people may have sufficiently important cognitive deficits to justify the implementation of this technology or alternately, their deficits may be too severe and hence require too many alternative interventions (e.g. supervision throughout the task, assistance to compensate some subtasks)." The findings of this paper revealed that flexibility of the solution and personalization options are crucial for such AAL technology to be more practical for the users.

2.1.1.2 Caregiver Requirements

Rashidi & Mihailidis (2013) suggest that one of the objectives of SH in assisted living is to reduce the caregiver's burden while emphasizing the significance of visualisation tools designed to allow the caregiver to assess daily activities and health information of the occupant. This data visualisation for caregivers can range from health data collected through wearables, information on physical habits of the occupant, to intelligent wellness evaluations performed by the SH system (Suryadevara & Mukhopadhyay 2014). A variety of different data visualisation techniques will therefore be development and tested as part of this PhD project.

Another study by Zarshenas et al. (2020) presented the healthcare providers' perspectives on the smart cooking assistant called COOK. Although the paper did not specifically investigate the benefits of activity tracking, feedback from one support worker revealed that they could benefit from the system if they could use it to track kitchen activities to ensure the person received their daily nourishment. Another aspect which was not investigated specifically in both the papers was feedback on the actual hardware of the solution and its associated impact on the person's ADLs. This provides an opportunity to gain further insight into the appropriateness and acceptability of SH sensors in the person's home as well as further build user profiles to gain an understanding on the diversity of carer and user needs which need to be addressed by such solutions as pointed out by Gagnon-Roy et al., (2020) and Zarshenas et al., (2020).

2.1.2 Views on Smart Home Development

Wilson et al. (2015) suggest that a clear understanding of the SH user base and a user-centric vision is missing from the research field that is being pushed by technology developers. They overview three broad views on SH – functional view, instrumental view, and socio-technical view, and suggest that Assisted Living is the most clearly resolved functional view of "better living" promised by SH. The paper also emphasises the importance of working with carers so that simple and low-tech solutions (such as making devices look familiar) can be identified. This is a SH requirement which may be less apparent as SH technology needs to be able to be integrated into the existing house and blend-in to the surroundings in order to appeal to home owners and keep the users feeling 'in control' (Balta-Ozkan et al. 2013). This is an important point made by the authors which is significant to this PhD for selection of sensors and other SH devices

It has also been suggested that usability and accessibility evaluation should be an important part of the design of SH user interaction systems (Queirós et al. 2015). The authors argue that certain SH products have failed to gain broad acceptance because their development processes are solely focused on technical specifications, instead of following a user-centric design methodology. The paper recommends a "...strong and active involvement of end users in al development phases, since the conceptual design and, later, during the validation and evaluation of prototypes". This view is reiterated by Wherton et al. (2015), who emphasize the importance of working with older users and their carers to co-design and co-produce SH products. The authors, however, accept that co-design with older adults can be challenging due to sensory impairment, cognitive difficulties, motility needs, fatigue, and lack of technical knowledge. They therefore recommend the use of visual aids and interactive tasks for co-design activities. Accordingly, for this PhD project we plan to work with users with long-term conditions in order to gain further insight into SH requirements and develop SH prompts and data visualisation techniques.

Furthermore, a paper by (Sriram et al., (2019) reviews studies on informal carers of persons with dementia involving the use of assistive technology. The authors report knowledge and acceptance, competence to use and ethical issues when using assistive technology. Key recommendations of the paper for future assistive technology highlight the importance of user-centred design and co-designed solutions. The authors suggest that the technology should match the needs of the user rather than "the person being moulded to match what technology is available for them". They also go as far as to suggest that the name of the technology should also be from the perspective of the person with dementia and their carer rather than the perspective of the manufacturer/developer. Although the paper states these recommendations specifically for technology to assist persons with dementia, it emphasises the importance of approaching such research from the carer and user's perspective rather than the technological perspective.

The importance of end-user engagement for technological development is clear from the literature reviewed in this section. Accordingly, this PhD will investigate the support requirements of people with LD by engaging directly with care providers. This will ensure that the technological solutions developed in this PhD are in accordance with the actual requirements of the care providers and their service users. This engagement will be focused on eliciting support requirements specifically for people with LD in the context of AAL systems, as majority of existing literature in AAL focuses on the ageing population.

2.1.3 Barriers to Smart Home Adoption

Literature reviewed in this subsection is divided into privacy and security, usability and accessibility, and reliability and safety. The literature includes concerns in these areas with regards to people with long-term conditions, which are used to inform the primary user engagement that will be conducted in this PhD

2.1.3.1 Privacy and Security

Morris et al. (2013) identified privacy concerns as the primary barrier to the adoption of SH technology by people with long-term conditions, specifically relating to cameras and monitoring systems. This view is shared by several other authors as well (Balta-Ozkan et al. 2013, Chalhoub et al. 2020) along with concerns regarding security such as the potential of leaving digital trails that others can access which could lead to break-ins. Morris et al. (2013) list various issues related to privacy, security, and trust such as data falling into the wrong hands, systems being compromised, monitoring systems feeling intrusive, and companies taking advantage of data for marketing and other purposes. For this PhD project these privacy and security concerns are an important factor to consider when it comes to SH sensor selection and the types of data and information that will be transmitted between devices.

2.1.3.2 Usability and Accessibility

Usability and accessibility are two inter-related issues that are affected by the complexity and user-friendliness of the SH. Usability refers to the capability of a product to be easily used, while accessibility describes the degree to which the product or service can be used by as many people as possible (Queirós et al. 2015). Intuitive user interaction is an important requirement of a SH for this, which includes providing a user-friendly interface and an overall architecture which allows the users to feel in control of their house. In the case of assisted living, accessibility barriers can vary for different users, such as poor vision, motor impairments, and other cognitive issues, which can drastically affect the type of user interface requirements (Rashidi & Mihailidis 2013).

One particular issue which increases the complexity of SH products is the (lack of) interoperability of different SH products and protocols (Balta-Ozkan et al. 2013, Queirós et al. 2015). This can be interpreted as a two-part issue; the first being the ability of different SH devices to work together (compatibility), the second being reassurance that the different devices will not interfere with each other's functionality. This suggests that it may be beneficial to stick to a single wireless protocol for as many sensors and devices as possible when developing holistic SH solutions. Additionally, it is important to investigate usability and accessibility issues which may be specific to the target user group of people with LD, and will therefore be part of the investigation conducted in this PhD.

2.1.3.3 Reliability and Safety

Reliability is concerned with the longevity of the device, consistent functioning, and avoiding unintended consequences (Balta-Ozkan et al. 2013, Wilson et al. 2015). The unintended consequences can range from low impact consequences such as TV turning off unexpectedly (inconvenience) to much higher impact consequences such as staircase lighting turning off while someone is walking (health risk). These issues can be a strong barrier for SH adopters, especially in the case of older adults who would be more vulnerable to these risks. For the purpose of the research conducted in this PhD, the implication of these findings are that it might benefit to limit the scope of the technological solutions to advanced monitoring/analytics and focus on interventions such as prompting, rather than directly controlling appliances in the home.

This section reviewed literature that provided insights into the development of AAL and SH technology. This literature re-informed the importance of user engagement in order to undertake technical development, as well as helped identify gaps which can be addressed with this engagement. The next section will focus specifically on SH sensors, in order to aid the sensor selection for this PhD.

2.2 Smart Home Sensors

2.2.1 Sensor Requirements

A primary requirement of SH technology in order to appeal to adopters is the need for the technology to 'fit' and blend into the existing house discretely (Balta-Ozkan et al. 2013, Choi et al. 2019). This is not just important for aesthetic purposes, but also for ensuring minimal disruption of everyday tasks performed by the occupants.

An important concept in SH technology is pervasive or ubiquitous computing, which includes embedding everyday objects with sensing and computing capabilities (Cook et al. 2009). Due to this, SH sensors are often battery powered in which case low power consumption is a huge priority for batteries to last as long as possible without needing replacement. Other SH sensor requirements are summed up by Viani et al. (2013) as scalability, low cost, integrability, reconfigurability, and multi-sensing capabilities. Furthermore, the authors emphasize on the importance of installation complexity, reliability, and low maintenance requirements.

2.2.2 Types of Sensors for Human Activity Recognition

Traditional SH sensors can be divided into three categories – Video and audio sensors, body-sensor networks and wearables, and passive sensor networks (Pal et al. 2016, Tunca et al. 2014). Recently, there has been research into non-traditional sensing techniques such as thermal imaging and device-free wireless localisation (Wang et al. 2017). There is also research into performing activity recognition by utilizing each type of sensor separately as well as utilizing multiple types of sensors simultaneously (Medjahed et al. 2011).

2.2.2.1 Video and Audio Sensors

With recent advancements in artificial intelligence for image processing, video-based solutions are able to provide the best context for performing activity recognition (Pal et al. 2016). However, several authors have raised concerns regarding privacy issues due to the intrusive nature of video cameras inside homes as well as the computational resources required for video processing (Tunca et al. 2014, Arning & Ziefle 2015, Liu et al. 2016). There is some ongoing research into resolving privacy issues through innovative solutions such as utilizing only extreme low resolution cameras to extract activity data (Ryoo et al. 2016).

Utilizing microphones around the house is another solution for performing activity recognition. Audio has been used in a variety of different ways, such as detecting water running through pipes (Basu et al. 2013), and combining audio-video recording for activity recognition (Vrigkas et al. 2015). However, the privacy concerns and computational requirements still remain primary barriers for both audio and video-based solutions.

2.2.2.2 Body Sensor Networks, Wearables, and Mobile Sensors

These are sensors that are physically placed on the user including wearables, mobile phone sensors, and other body-worn devices (Chen et al. 2020). Most smartphones are equipped with a multitude of sensors such as accelerometer, gyroscope, proximity sensor, and GPS which can be utilized to perform activity recognition. Other wearable devices can be used to monitor physiological data such as body temperature, heart rate, and blood pressure which can be combined with other sensor data to perform further wellness evaluation. Advantages of using wearables include that they can be worn outside the house, helping monitor the individual's activities throughout the day, as well as providing physiological data which can be difficult to monitor otherwise. The downside of using these type of sensors is that they are often viewed as obtrusive and elderly people may forget to wear them every day and charge them frequently (Pal et al. 2016).

2.2.2.3 Passive and Ambient Sensor Networks

Passive and ambient wireless sensor networks consist of sensors embedded in the environment of the user which are passive in nature, meaning they can sense the environment without directly tracking the user (Chen et al. 2020). This includes Passive Infrared Sensors (PIR sensors) for detecting motion, pressure sensors for detecting presence, contact sensors on doors/cupboards, temperature sensors, luminosity sensors, etc. (Roggen et al. 2013). The concept of ambient sensors is most in-line with that of ubiquitous or pervasive computing, as it involves incorporating everyday objects with sensing and computing capabilities. Due to this, passive sensors are not restricted to a specific hardware or protocol, for example, as mentioned previously, one study deployed audio sensors to detect water flow in pipes which can be viewed as a passive sensing technique (Basu et al. 2013).

Passive sensors can often work with low computational costs, less complex data processing algorithms for information extraction, and low network requirements when compared to video based solutions (Li et al. 2017). Researchers also regard passive sensors to be less obtrusive and as posing less of a threat to user privacy compared to other types of SH sensors, and have emphasized on attributes such as flexibility, scalability, and integrability (Basu et al. 2013, Viani et al. 2013). On the other hand, Cardinaux et al. (2011) argue that passive sensing requires a large number of battery operated sensors to be embedded in the room, which can increase maintenance costs and affect the activity recognition algorithms if the performance of the sensors vary.

There are various low-bandwidth networking protocols for passive sensors, with Z-Wave and Zigbee being two of the most popular commercially and in academic research (Risteska Stojkoska & Trivodaliev 2017). Both of these protocols support mesh networking, meaning that each node of the network also extends the network to other nodes, providing a wide coverage without the need for a signal booster.

2.2.2.4 Other Non-traditional Techniques

Recently, there has been research into innovative solutions that could replace the need for traditional SH sensors, such as advances in Device-Free Wireless Localisation and Activity Recognition (DFLAR). These techniques are highly unobtrusive as they only utilize wireless signals to perform localisation and activity recognition (Wang et al. 2017), however they are susceptible to interference from other wireless devices.

Another technique which serves as an alternative for traditional video-based solutions includes the use of thermal cameras, specifically low resolution thermal cameras which conserve the subject's privacy but provide enough information for machine learning models to detect complex movement. Burns et al. (2019) used two low resolution thermal cameras to detect a person's movement around the room as well as recognise actions such as opening/closing a fridge with an accuracy of 91.47%. Furthermore, Uddin & Torresen (2018) claim that it is more useful to use thermal cameras as opposed standard RGB cameras as the former can detect human activity even in dark environments where an RGB camera would fail to produce visually understandable images. Therefore, thermal cameras are a promising alternative to standard RGB video cameras for providing rich information for activity recognition without compromising the privacy of the user. Additionally, as these are low resolution thermal cameras with a low frame rate, the computing power required to process the frames provided by these thermal cameras are much lower compared to standard video-based solutions.

This section provided an overview of the various types of sensors which can be utilised for performing HAR. Specifically, the advantages and disadvantages of the sensors were revealed, which in turn will aid with narrowing down the types of SH sensors to be used for the user engagement study in order to receive further feedback. The next subsection reviews existing techniques for utilising data from these sensors and performing HAR.

2.3 Data Processing and Machine Learning

This section reviews the existing research into data processing and machine learning techniques that have been deployed for SH data.

2.3.1 Activity Recognition Techniques

In order to provide assistance in a SH environment, activity recognition is crucial for the system to identify the task the individual is currently undertaking (Okeyo et al. 2014). As a SH is embedded with sensors, this sensor data can be used to extract contextual information about the task the occupant is undertaking, which is often fused with sensor data from mobile phones and wearables to perform activity recognition. Existing activity recognition approaches fall into two categories: data-driven and knowledge-driven (Hussain et al. 2020). These two approaches, along with their advantages and disadvantages are described in more detail in the following sections.

2.3.1.1 Data-Driven Techniques

Data-driven activity recognition is a more traditional approach which utilize supervised or unsupervised learning techniques to extract and activity model from a pre-existing dataset. Existing studies have included utilizing statistical and probability analysis methods along with clustering and segmentation techniques to extract activity models present in the dataset (Okeyo et al. 2014, Wan et al. 2015). Data-driven approaches have been well tested in existing literature and shown promising results. However, they generally require large amounts of training datasets (Suryadevara & Mukhopadhyay 2014) and are usually suited to single occupancy scenarios (Chen et al. 2012).

2.3.1.2 Knowledge-Driven Techniques

Knowledge-driven approaches utilize ontological modelling along with a logic-based approach to perform activity recognition (Okeyo et al. 2014). This requires knowledge engineers or domain experts to utilize knowledge engineering techniques to specify activity models explicitly. Certain knowledge-driven approaches also then employ pattern recognition techniques to perform activity recognition. These approaches usually take available sensor data as input and then compare them to predefined explicit activity models to recognise the activity being performed. Knowledge-driven approaches have an advantage over data-driven approaches as they require less training data, and can be vital in unconstrained environments, where enough data may not be available or it may suffer from occlusions (Vrigkas et al. 2015). However, knowledge-driven activity recognition is a relatively newer area of research when compared to its data-driven counterpart and often does not produce as robust results. Another drawback of knowledge-driven approaches is that the activity models are usually static, and cannot evolve or automatically adapt to user's specification after they have been defined (Azkune et al. 2015).

These findings indicate that a combination of knowledge-driven and data-driven techniques may provide the optimal configuration for performing HAR. As knowledge-driven approaches reduce the amount of training data required, it may be possible to utilise aspects ontological modelling for performing HAR. The specific methodology for this will be investigated in chapter 6 of this thesis.

2.3.1.3 Offline Activity Recognition

Offline activity recognition refers to activity recognition which is performed on a dataset that has been already collected (as opposed to streaming real-time sensor data). These techniques often take more time to process so they cannot be used on real-time sensor data, but they can provide more information and analysis of the sensor data than their online counterparts (Incel et al. 2013). A major application of offline activity recognition systems is health monitoring and wellness evaluation in AAL scenarios as discussed below (Suryadevara & Mukhopadhyay 2014).

In order to perform HAR, periods of sensor data events that may represent activities must be extracted first. Traditional approaches for this include the use of sliding time and sensor windows as used by Yala et al. (2015), Krishnan & Cook (2014). These sliding windows are generally used for training supervised learning systems when activity labels are present, as the sliding windows can be chosen based on the activity labels present in the data, and windows containing noise can be removed manually. However, due to this, they are not as well suited for unlabelled data as it would be difficult to identify windows that contain noise. The lengths of these windows are also often fixed which makes the activity recognition system highly sensitive to variance in the distribution of sensor events throughout the day. Therefore, it is important to investigate alternative approaches for extracting periods of sensor data events of variable lengths.

An alternative approach is presented by Soulas et al. (2015) for discovering "episodes" of user activities along with their periodicity and variability. The authors use an episode length of 30 minutes which essentially acts as a time window for extracting sensor data which may belong to an episode. However, this is left as a parameter to be set by the user depending on their daily habits. Along with this, the authors also define five additional parameters which need to be set by the user and the user's physician in order for the algorithm to work. The authors acknowledge that setting unsuitable parameters can lead to missing interesting information and other automated candidate episode generation techniques need to be investigated. Nevertheless, the authors' paper highlights the need for HAR algorithms that do not require priori knowledge on the user. They also provide an analysis into the variability and repeatability of user behaviour present in the public SH datasets, however their approach for this requires considerable hand-tuning of the learning methods.

The sliding window approach as discussed in this section is a data-driven technique for streaming sensor data; this thesis investigates the use of a more knowledge-driven approach as an alternative for extracting more useful features from the sensor stream in chapter 6.

2.3.1.4 Health Monitoring and Wellness Evaluation

Data fusion of SH sensor data and wearables have led to research into a variety of offline activity recognition and health monitoring systems. This has included systems that help with rehabilitation of older adults who have been discharged from emergency-departments following cognitive decline. Some researchers have also investigated the development of emergency response systems which perform fall detection from the data fusion (Liu et al. 2016).

Another utilization of SH sensor data is performing wellness evaluation. One such approach is presented by Fiorini et al. (2017) in which the authors evaluate a "busyness" measure of the participants which relates to the way user activity is distributed over a certain period of time. A number of different machine learning techniques were employed for this including Multiclass Support Vector Machine (SVM), K-Means clustering, and SOM along with PCA to reduce set features. This "busyness" measure is then analysed to classifying the participants in the test set into two classes - older persons and persons with cognitive impairment. After establishing the baseline over 55 days, the approach presented by the authors achieved an accuracy of over 90% on the test set which consisted of 23 days. This provides an interesting approach utilizing a minimal amount of SH sensors to perform wellness evaluation of the users.

Offline activity recognition and data analysis are also used for performing data visualisation for the carer. Mulvenna et al. (2011) provide a good overview of different applications of data visualisation in AAL and SH environments. This PhD will further investigate the utility of such visualisations and wellness evaluation techniques for supporting people with LD, through the user engagement detailed in chapter 3.

2.3.2 Online and Adaptive Activity Recognition

Online activity recognition refers to techniques that utilize machine learning methods to perform activity recognition in real-time on streaming sensor data. This form of HAR is crucial for providing real-time support to the user. The development of online and adaptive HAR systems can lead to interventions such as prompting as well as real-time support through assistive robotics.

Yala et al. (2015) present two methods that utilize an incremental SVM for the purpose of extracting features from a sequence of sensor events and use clustering handling missing activity labels from the dataset. This online approach uses a sliding window that encodes the preceding sensor events in order to classify them. The sensors included in this paper are passive sensors such as motion and door sensors. The data is first divided into segments or windows suitable for the activity recognition, from which features are computed and used as an instance for learning or testing. The authors then mention the various techniques for segmenting streaming data in existing literature before deciding on sensor-based windowing as the method to be implemented. In this method a sliding window of a length of 6 events is used for obtaining the sensor window. Feature extraction is achieved through a modified sensor dependency method and the last-state sensor method, both of which are contributions of the authors. Missing activity labels are determined through clustering sensor events into existing activity labels as well as discovering new classes of activities. The proposed techniques were trained and tested on the Aruba dataset from the Washington State University's Center of Advanced Studies In Adaptive System (CASAS) test bed which included over four months of data. This work provides a methodology for working with public SH datasets. The research presented in chapter 4 of this thesis is also based on a public SH dataset as used by Yala et al. (2015), however, an alternative to sliding windows for extracting more useful sequences of sensor events is presented.

Saunders et al. (2016) provides an interesting approach that utilizes an intuitive "teach me - show me" environment for scheduling and planning tasks and programming robot behaviour. The paper begins by introducing the need of a learning environment to enable personalisation of assisted living robots as the authors argue that scripted robot behaviour is not enough in order to adapt and provide support to the occupant. The same can be said about AAL in general, which is why adaptability is a crucial functionality. The authors then present a "teach me" interface which is used to teach the robot new behaviours by specifying "what" and "when" (action and preconditions). A "show me" interface is used to teach the robot to recognise a new activity by physically carrying out the activity while the robot is in "show me" mode. This avoids the need of pre-labelling activities which can be costly. The new activity taught through the "show me" interface can then be exploited by the "teach me" interface. These two interfaces combine to provide a methodology for self-labelling of both, user activities and configuration of robot behaviour. However, one of initial points raised by the authors was related to adaptability of assisted living technology over time, but the behaviour and activity recognition capabilities of the "teach me - show me" system do not evolve over time adapting to change in human behaviour. This would therefore require re-labelling of activities if they are performed differently in the future which can be time consuming. It can be observed that the combination of a similar user interaction methodology along with an adaptable machine learning approach would be an effective HAR solution. This has special significance to the research presented in chapter 6 of this thesis, where certain a-priori information is received through user interaction in order to develop an adaptable HAR system.

Kabir et al. (2015) propose an activity recognition system that utilizes a Back Propogation Neural Network (BPNN) for prediction and Temporal Difference (TD) class of Reinforcement Learning (RL) for adaptation. The system architecture presented in the paper consists of three layers - sensor layer, middleware layer, and application layer. Sensor layer is the layer consisting of the various sensors deployed throughout the house. The middleware layer consists of the context modelling context reasoning, and the controlling of sensors, appliances and devices based on the output of the context-aware application layer. The latter is the main focus of the paper which is made adaptive through the use of machine learning. The BPNN has five inputs - person ID, location, time, day, and activity, and five outputs - sleeping service, morning call service, dinning service, entertainment service, and guarding service. The proposed solution in the paper accepts both explicit and implicit user feedback to generate positive or negative reward values for RL. Explicit feedback is provided directly by the user while implicit feedback is calculated as follows –

$$\text{Feedback} = \frac{\text{Time user stayed with service}}{\text{Total time for service}} - 1 \qquad (2.1)$$

where the "Total time for service" is a predefined time period in which no user response is interpreted as a negative reward (equation 2.1). To make the system adaptive, TD RL is deployed as an unsupervised machine learning algorithm. The action value Q(s,a) represents the satisfaction of the user with the action a given state s, and after reaching a certain threshold leads to the addition of the corresponding context/service as new training data for the neural network as follows –

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma.Q(s',a') - Q(s,a)] \tag{2.2}$$

where α is the learning rate, γ is the discount rate, and r is the reward (equation 2.2). The training sets for the BPNN are stored in a knowledgebase, which is updated following the above process. The authors only focus on using pre-defined scenarios or services, but the use of a BPNN along with TD RL provides a unique approach for building, choosing, and adapting policies in a SH.

The concept of utilising user feedback, specifically the time taken for the user to provide feedback as a reward function provides a novel methodology for developing an adaptive HAR system. In this thesis, an HAR system for tracking activities in real-time is presented in chapter 6, where a similar approach to utilising the time taken by the user to respond to prompts is investigated as part of the HAR system.

2.4 Summary

From the literature review presented in this chapter, the importance of involving end-users in the early design process has been highlighted. This makes it crucial that in addition to literature review, stakeholder engagement must also be conducted for answering RQ1 and RQ2, before proceeding with technical development to answer RQ3 and RQ4. For this development, it is evident that the HAR systems must be unsupervised or semi-supervised as well as adaptable to changing user behaviour in order to be practical for deployment. It is also clear that privacy and obtrusiveness are big factors when considering sensors for HAR, and thus WSN would be preferable over BSN and video-based solutions. This makes it crucial to engage with stakeholders to verify the acceptability of the sensors reviewed in this chapter. Additionally, performing complex HAR with ambient WSN while using unsupervised and semi-supervised techniques has proven challenging. It is also evident that thermal cameras are a competent alternative to standard video-based solutions, but most of the existing research that utilizes thermal cameras is focused on pose detection or single component HAR (such as sitting at a table), and not recognising complex activities such as meal preparation (Burns et al. 2019). Therefore, this provides a novel opportunity to fuse data from multiple types of sensors such as ambient WSN and thermal cameras in order to extract more context rich information for semi-supervised HAR while still conserving user privacy.

Chapter 3

Carer and Service User Requirements

Chapter redacted for copyright reasons.

Chapter 4

Discovering Activity Patterns from Sensor Data using a Public Dataset

An important requirement of care providers as presented in the previous chapter was to be able to track and identify changes in the service user's routine using SH sensors, prioritising kitchen activities. Accordingly, this chapter investigates the utility of unsupervised machine learning and data visualisation techniques in order to identify patterns of user's activities in the kitchen over a 12 week period from a public SH dataset. The work also takes into account the feedback received on SH sensors from the interviews conducted in the previous chapter, by including it as a criteria for the dataset selection. The focus of this chapter is on answering Research Question 3 and completing Research Objective 3.1:

RQ3. How can SH sensor data be utilised for informing care providers about changes to the service user's kitchen activities?

Research Objective 3.1: *Utilise smart-home sensor data for extracting information that can be used to identify changes in a person's kitchen activities. The information extracted from the dataset should reflect on the findings of RQ1 and RQ2, relating to the care provider's requirements of actionable information.*

The chapter begins by providing an introduction to the study, before building upon the literature review in section 4.2. Section 4.3 provides a description of the Aruba CASAS dataset (Cook 2012) as used in the study; section 4.4 describes the methodology; section 4.5 presents the results and discussion; and finally section 4.6 summarises the outcomes relating them to RQ3.

4.1 Introduction

As explained in Chapters 1 and 2, the challenge in using unlabelled passive and ambient sensors for HAR is to find practical approaches which can provide meaningful information that can be used to support timely interventions based on changing user needs without the overhead of having to label the data over long periods of time. Accordingly, Research Objective 3.1 can be further articulated as the two objectives listed in Table 4.1.

Table 4.1: Key objectives

#	Objective
1	Extract activity information from unlabelled SH sensor data using unsupervised techniques.
2	Visualise the extracted information to identify shifts in patterns of user activities.

The work presented in this chapter achieves these objectives through a unique data pre-processing technique utilising Kernel Density Estimation (KDE) (Rosenblatt 1956) together with t-Distributed Stochastic Neighbour Embedding (t-SNE) (van der Maaten & Hinton 2008) and Uniform Manifold Approximation and Projection (UMAP) (McInnes et al. 2018) for visualising changes in user activities. The methodology is developed and tested on the Aruba CASAS smart home dataset and focusses on discovering and tracking changes in kitchen-based activities. The traditional approach of using sliding windows to segment the data requires a-priori knowledge of the temporal characteristics of activities being identified. In this work we show how an adaptive approach for segmentation, KDE, is a suitable alternative for identifying temporal clusters of sensor events from unlabelled data that can represent an activity. The ability to visualise different recurring patterns of activity and changes to these over time is illustrated by mapping the data for separate days of the week. The study then demonstrates how this can be used to track patterns over longer time-frames which could be used to help highlight differences in the user's day to day behaviour. By providing a means to intuitively examine a specific individual's data for temporal changes in activity over varying periods of time from unlabelled sensor data opens up the opportunity for carers to then initiate an enquiry. This is seen as an accessible first step to enable carers to initiate informed discussions with the service user to understand what may be causing these changes and suggest appropriate interventions if the change is detrimental to their well-being.

The next section builds upon the literature review from Chapter 2 to provide context for the choice machine learning and data visualisation techniques utilized in this study.

4.2 Background and Prior Work

This section reviews machine learning techniques for extracting information from SH sensor data as well as unsupervised dimensionality reduction and visualisation techniques.

4.2.1 Techniques for Extracting Activity Information from Unlabelled SH Sensor Data

In order to perform HAR, periods of sensor data events that may represent activities must first be extracted. Traditional approaches for this include the use of sliding time and sensor windows as used by Yala et al. (2015), Krishnan & Cook (2014). These sliding windows are generally used for training supervised learning systems when activity labels are present, as the sliding windows can be chosen based on the activity labels present in the data, and windows containing noise can be removed manually. However, due to this, they are not as well suited for unlabelled data as it would be difficult to identify windows that contain noise. The lengths of these windows are also often fixed which makes the activity recognition system highly sensitive to variance in the distribution of sensor events throughout the day. Therefore, it is important to investigate alternative approaches for extracting periods of sensor data events of variable lengths.

An alternative approach is presented by Soulas et al. (2015) for discovering "episodes" of user activities along with their periodicity and variability. The authors use an episode length of 30 minutes which essentially acts as a time window for extracting sensor data which may belong to an episode. However, this is left as a parameter to be set by the user depending on their daily habits. Along with this, Soulas et al. also define five additional parameters which need to be set by the user and the user's physician in order for the algorithm to work. The authors acknowledge that setting unsuitable parameters can lead to missing interesting information and other automated candidate episode generation techniques need to be investigated. Nevertheless, the paper highlights the need for HAR algorithms that do not require a priori knowledge on the user. They also provide an analysis into the variability and repeatability of user behaviour present in the public SH datasets, however their approach for this requires considerable hand-tuning of the learning methods.

In the work presented by Gupta & Caleb-Solly (2018), sensor data was analysed by room only, and treated as 1D time series data per room, only comprising of sensor event timestamps. An alternative approach to sliding windows in this case would be to find and extract periods of high-density present in the sensor data which could potentially represent activities. As the sensor data can be treated as 1D time series, Kernel Density Estimation (KDE), as first proposed by Rosenblatt (1956), can be a powerful tool for extracting periods of sensor events which can potentially represent an activity. KDE is a non-parametric method for estimating the probability density function of a random variable, and as such can be used to detect time periods of high-density present in 1D data. This overcomes the issue of deciding the size of sliding windows and has the added benefit of identifying only high periods of sensor activity and disregarding the rest as noise. KDE has two parameters - kernel function and the bandwidth. The kernel function must be chosen based on the properties of the data, while the bandwidth can be selected using Silverman's rule (Silverman 1986). As these parameters can be derived statistically, KDE can be a potential alternative to traditional fixed-size sliding windows for extracting sensor data.

4.2.2 Techniques for Visualising the Extracted Activity Information

Once periods of sensor data are extracted, the next step is visualising the data. In recent years, new visualisation techniques have been introduced which have superseded existing techniques such as Self-Organising Maps (SOM's) and Principal Component Analysis (PCA) in certain applications. These visualisation techniques include t-Distributed Stochastic Neighbour Embedding (t-SNE) (van der Maaten & Hinton 2008) and Uniform Manifold Approximation and Projection (UMAP) (McInnes et al. 2018), both of which are non-linear dimensionality reduction techniques. T-SNE has often been the primary choice for researchers for visualising high dimensional data in 2D and is noted for preserving the local structure of the data. UMAP on the other hand is a much newer technique and is capable of preserving both local and global structure of the data (Becht et al. 2018). These techniques are particularly relevant when dealing with unlabelled data, as they can help to discover whether there are any meaningful features and potential clusters present. However, it must be noted that even though both t-SNE and UMAP are both useful choices for visualisation, clustering based on their output is generally not recommended, as density information is often lost during the process (Wattenberg et al. 2017). An interesting technique is also presented by Fiorini et al. (2017), where radar graphs were constructed from motion sensor data which can be used to facilitate a quick visual analysis of the sensor data. This technique can be used in conjunction to visualisation techniques such as UMAP to gain further insight into the sensor data.

To summarise, in this section the potential benefits of KDEs to replace sliding windows for extracting sensor data and the use of t-SNE/UMAP for visualising unlabelled data have been highlighted. The next section provides a description of the Aruba CASAS smart home dataset, which will be used for developing, as well as testing the unsupervised learning methodology presented in this paper.

4.3 Selection and Description of Public Smart Home Dataset

This section provides details of the selection process for the SH dataset, the description of the selected dataset, and activities which were selected for use in this study.

4.3.1 Dataset Selection

For this research we focused on the Washington State University's Centre for Advanced Studies in Adaptive Systems (CASAS) dataset collection (Cook 2012). This collection comprises a range of labelled, partly-labelled, or unlabelled activity data, collected over varying time periods. The activities in these datasets are scripted or unscripted. The work presented in this paper is focussed on unscripted "daily life" datasets. Additionally, datasets which use BSNs or video cameras were not considered as the focus in this research is on utilizing less intrusive WSNs, such as motion sensors as identified in the previous chapter. Five public datasets met these criteria. A further search was conducted for these five CASAS datasets on IEEE with keywords ((((Smarthome) OR smart-home) AND 'nameofdataset') AND CASAS). This revealed the Aruba dataset as the most frequently used dataset with 31 search results, and Milan as the second most frequently used with 15 search results. Based on this, both Milan and Aruba were shortlisted. The Aruba dataset has a total of 220 days of continuous data, while the Milan dataset has a total of 72 days of data. However, Milan is missing 11 days of data, while the Aruba dataset has continuous data with no missing days. The missing days could affect the performance of the HAR algorithm as it is crucial to analyse consecutive days in order to pick up repeating activity patterns. The Aruba dataset was therefore selected for developing and testing the unsupervised learning techniques presented in this paper.

4.3.2 Aruba Dataset Description

The Aruba dataset consists of data from a total of thirty-nine sensors, out of which thirty-four are PIR sensors and five are temperature sensors. In this paper only the PIR sensor data, which represent the occupant's physical movement in the vicinity of the sensor, is analysed. Therefore, after excluding temperature sensor data over the period of 220 days, a total of 1,602,980 sensor events are present out of which 849,579 sensor events (53%) are not annotated with any activity labels in the dataset. Previous studies have often discarded these unlabelled sensor events when performing HAR as activities detected using the unlabelled data cannot be verified (Yala et al. 2015).

4.3.3 Activity Selection

There are a total of 11 activity labels present in the Aruba dataset (Figure 4.1). The primary kitchen activity labels are "Meal_Preparation" and "Wash_Dishes. There are a total of 1606 instances of the

"Meal_Preparation" activity and only 65 instances of the "Wash_Dishes" activity. In previous studies, this imbalance has caused classifiers to misclassify the "Wash_Dishes" as "Meal_Preparation" activity (Yala et al. 2015).

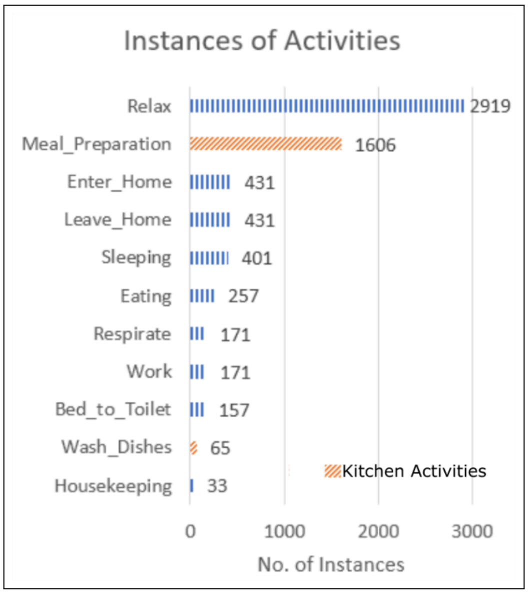

Figure 4.1: Total instances of activity labels in the Aruba Dataset

As this study is focused on kitchen activities, only kitchen sensor data was analysed, which includes "Meal_Preparation" and "Wash_Dishes" activity labels. These event data represented by these two labels was further analysed to verify which sensors were associated with these labels in the Aruba dataset. Both "Meal_Preparation" and "Wash_Dishes" labels were primarily based on only kitchen sensors (five PIR sensors) being triggered over the entirety of the dataset; all other sensors in the house were associated with less than 5% of both the activity labels. This supports the approach previously presented by Gupta & Caleb-Solly (2018), in which only kitchen sensor data was analysed when performing HAR for kitchen activities, considerably reducing the noise and amount of the data required to be processed. It should be noted that no unlabelled sensor data was removed by hand, as it was left to the unsupervised machine learning techniques to identify noise. As stated previously, this is different to previous studies by other researchers using this dataset, who removed all unlabelled data from the analysis as the activity represented by that data could not be verified Yala et al. (2015). The approach of retaining unlabelled data better reflects a real-world scenario, where a dataset is likely to contain unlabelled instances.

4.4 Methodology

This section outlines the methodology followed for this study which includes extracting activity information (as temporal clusters) using Kernel Density Estimation from sensor data, feature selection, and the use of data visualisation techniques. This study performs two different data analyses, the first analysis is aimed at veryfing the results of the KDE sensor data extraction technique as outlined in section 4.4.1, the second analysis is aimed at creating visualisations from the extracted data as detailed in sections 4.4.2 and 4.4.3. All the algorithms were written in Python using various machine learning libraries which are referenced throughout the paper.

4.4.1 Extracting Temporal Clusters of Sensor Events using KDE

Over the past decade, as research into AAL and SHs has grown, various new concepts and terminology have been introduced to the field. In this study some of these existing concepts have been further developed, such as that of a temporal cluster. This study presents a method for extracting periods of high-density present in the temporal sensor data, which have been defined as temporal clusters (Figure 4.2). Therefore, a temporal cluster (**TC**$_i$) is a set of sensor events occurring close together {$\mathbf{s}_1$, $\mathbf{s}_2$, $\mathbf{s}_3$, ... $\mathbf{s}_n$} that could potentially represent an activity.

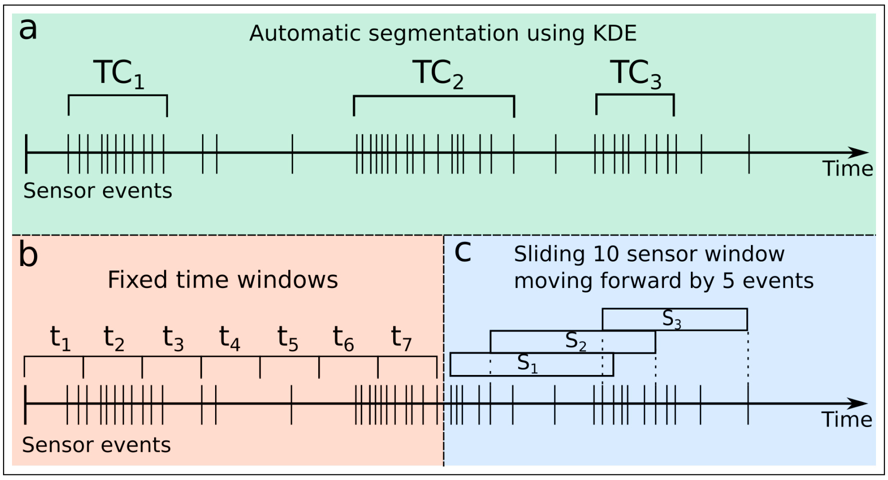

Figure 4.2: **a)** Sensor segmentation using KDE to extract Temporal Clusters (**TC**$_i$), **b)** fixed time windows (**t**$_i$), and **c)** sliding sensor windows with a length of 10 sensor events and sliding forward by 5 sensor events (**s**$_i$)

For developing this temporal cluster extraction approach using KDE, the Aruba dataset was divided into a training and test set. Days 10 to 42 were used as the training set and days 53 to 81 were used as the test set. As we see later in this study, temporal clusters are tested with the dataset by comparing how many instances of "Meal_Preparation" activity were extracted by this technique. However, for the purpose of extracting patterns from the sensor data in the final data analysis, temporal clusters are used with a view to identify activity patterns which might not have been represented by the user activity labels in the dataset, but could still represent specific user activities or behaviour. Meaning that periods of sensor data extracted by temporal clusters which do not represent an activity label in the dataset are still viewed as relevant information.

KDE requires the selection of a kernel and the kernel's bandwidth. After analysing the training set, the Epanechnikov kernel (Epanechnikov 1969) was empirically selected for the algorithm. The Silverman's rule (Silverman 1986) for automatically selecting the bandwidth was also empirically adjusted to:

$$\text{bandwidth} = 0.07\hat{\sigma}n^{-1/5} \tag{4.1}$$

where $\hat{\sigma}$ is the standard deviation of the sample and n is the sample size. The KDE temporal cluster extraction technique is illustrated in Figure 4.3. This figure shows an example of KDE temporal cluster extraction process for the morning hours of 8 am to 10 am for a selected day from the Aruba dataset. For the experiment, KDE was used to generate a density curve for the whole day which was then used to extract temporal clusters as shown. Following this, all the sensor events included within the mid-height of the peaks were extracted as a single temporal cluster (Figure 4.3d). The mid-height of the peaks were calculated as 50% of the height of the peak relative to whichever comes first - the last local minima before a local maxima higher than the current peak, or the global minima. This ensures that a peak which is higher than other peaks that follow it, extracts a larger temporal cluster as is the case for peak 2 in Figure 4.3d. Mid-heights that contained less than two sensor events or lasted less than 60 seconds were discarded as noise. This 60 second threshold value for noise along with the mid-height of the peak were selected after conducting the analysis with the training data.

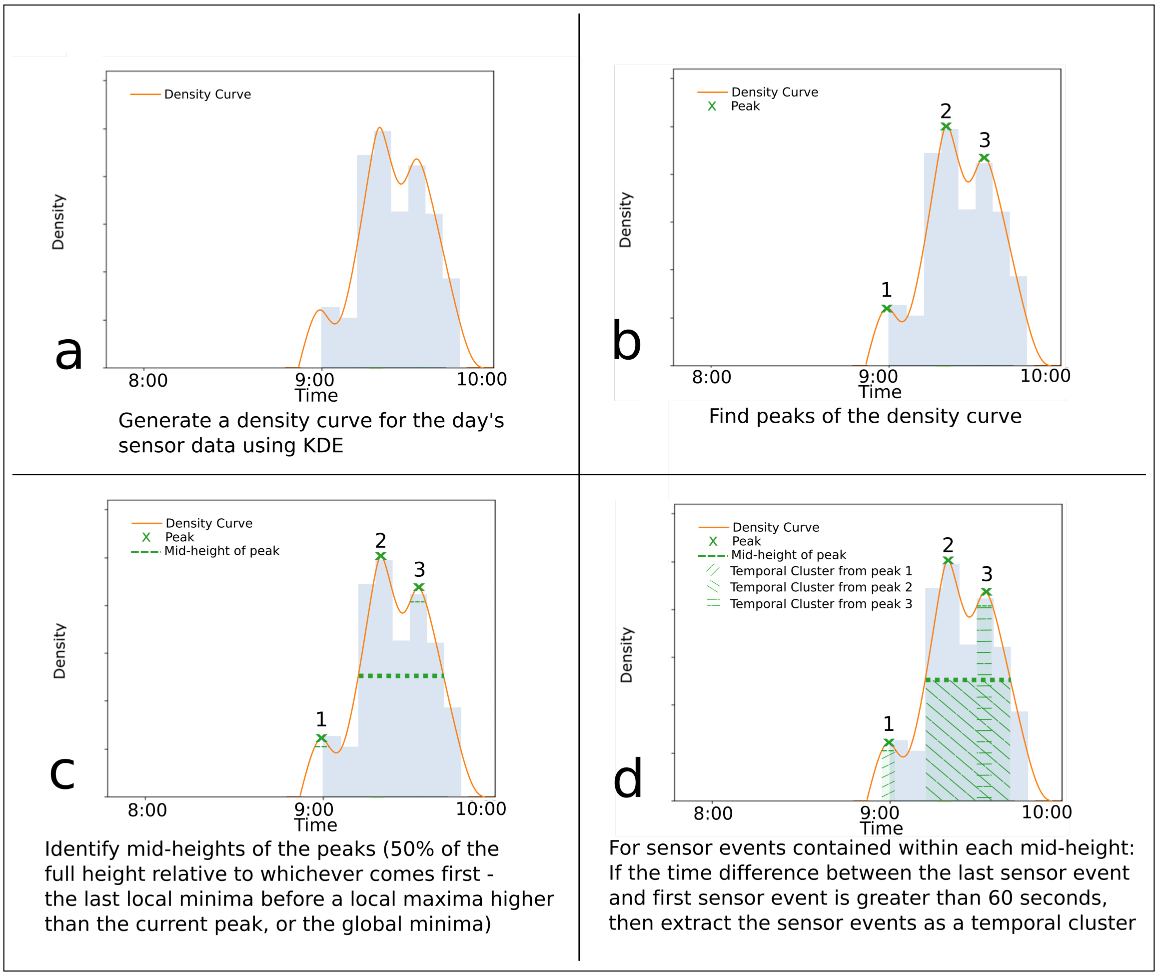

Figure 4.3: Three temporal clusters extracted from the density curve generated using KDE for a single morning, overlaid with a histogram of sensor event timestamps.

A feature of using KDE is that it can also discover temporal clusters which may represent interleaved and overlapping activities. An example of this can be seen in Figure 4.3d where temporal cluster from peak 3 overlaps a larger temporal cluster from peak 2. The stats module from the SciPy was used to perform KDE in Python (Jones et al. 2001).

4.4.2 Feature Selection

The next step was to select features from the extracted temporal clusters which could help identify patterns in the user activity. These features are listed in Table 4.2, and build upon prior works which have utilized sliding windows (Yala et al. 2015, Soulas et al. 2015) along with the work presented by Gupta & Caleb-Solly

(2018).

This feature set consists of eight features, the first three being – duration (length) of the temporal cluster, the variance in each temporal cluster based on timestamps of the sensor events, and start-time of the temporal cluster. The start-time was corrected to the hour closest to the first timestamp of the temporal cluster. The last five features were total number of events from each sensor separately in the Kitchen. All features were normalised between 0 and 1.

Table 4.2: Features selected from each Temporal Cluster

#	Feature
1	Duration of Temporal Cluster
2	Variance of Temporal Cluster
3	Start-Time of Temporal Cluster (Hour)
4	Total Sensor Events for Kitchen Sensor 1
5	Total Sensor Events for Kitchen Sensor 2
6	Total Sensor Events for Kitchen Sensor 3
7	Total Sensor Events for Kitchen Sensor 4
8	Total Sensor Events for Kitchen Sensor 5

4.4.3 Visualisation using UMAP

In order to visualise the behavioural changes by day-of-the-week, UMAP was performed to generate data points in a 2-dimensional space from the 8-dimensional feature sets of the temporal clusters. It was hypothesised that using a day-of-the-week level of granularity might help to better track changes in the longer term, because as shown in Fiorini et al. (2017), there can be marked differences between weekday and weekend routines.

A 12-week (3 month) period was considered which ensured that there were enough data points for identifying repeating patterns for each day of the week. Four such periods of 12 weeks were then compared to verify whether the activity patterns persist and whether any slight changes were apparent. This means analysing four sets of 12 Mondays, 12 Tuesdays, and so on. The first three of these periods were overlapping and moving forward by 1 week at a time as follows – weeks 2 to 14, 3 to 15, and 4 to 16. This was done with a view to analyse small shifts in the user's daily routine. The last period did not overlap with the first three periods and consisted of weeks 17 to 29. This was done to determine whether, if at all, user behaviour may have changed after a longer non-overlapping time period.

Figure 4.4a shows an example of Mondays for weeks 4 to 16 for UMAP. The parameter "n_neighbours" was set to 15 and "min_dist" was set to 0.1 empirically.

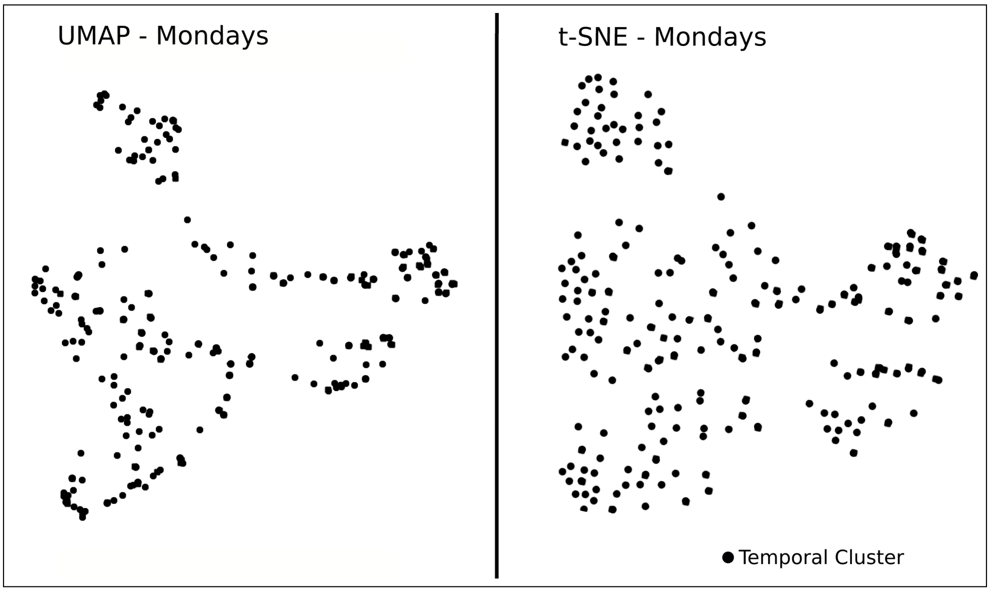

Figure 4.4: (a) Top – UMAP, (b) Bottom – t-SNE (Both projections are for weeks 4 to 16)

T-SNE (Figure 4.4b) was also performed for comparison using the same dataset to verify that the UMAP plot does not contain spurious artefacts. The perplexity parameter of t-SNE was determined empirically and set to 25.

It can be seen in Figure 4.4 that the plots created by UMAP and t-SNE are visually similar. T-SNE plots also appeared to have a less visually discernible morphology as can be seen in Figure 4b, which makes them harder to interpret for the sensor data. It must also be noted that t-SNE is very sensitive to the perplexity parameter and as such makes it difficult to obtain consistent and reliable results (Wattenberg et al. 2017). For these reasons, UMAP was favoured for visualising the patterns of activities clusters.

4.5 Results and Discussion

This section presents the results of the KDE for extracting temporal clusters, as well as the UMAP visualisations. The first analysis is in accordance to objective 1 from Table 4.1 while the second analysis is focused on objective 2.

4.5.1 Analysis 1: KDE - Extracting Temporal Clusters

This section presents the results of the KDE temporal cluster extraction technique performed on the Aruba test dataset for each day individually. The goal of this analysis is to achieve objective 1 from Table 4.1, that is, extract activity information from unlabelled SH sensor data. The KDE temporal cluster extraction technique was tested on a consecutive 28-day period. Using the KDE temporal cluster extraction technique, a total of 454 temporal clusters were extracted for this period (Table 4.3). These temporal clusters included 100% of the labelled activities present, within an error of + or - five minutes as compared to the timestamps of the activities in the dataset. 211 additional temporal clusters (46% of the total) were also discovered, which were not associated with an activity label.

Table 4.3: KDE results for the test period: 53 to 81 (total 28 days).

Results	#
Labelled activities in the test period	243
Temporal clusters extracted (labelled)	243
Temporal clusters extracted (unlabelled)	211
Total temporal clusters extracted (unlabelled)	454

Researchers in the past have either labelled the unlabelled periods of sensor activity as an additional "Other" activity or have removed them completely (Yala et al. 2015). In such studies, the accuracy of the activity recognition system is significantly impacted due to the presence of noise in the unlabelled sliding windows being classified. In the study presented in this paper, temporal clusters that contained unlabelled data were not removed but were included in the analysis as they could potentially represent activities that are not labelled, yet are of significance in representing the user's behaviour. Periods of low sensor activity in the Kitchen, which can be viewed as noise and not pertaining to any important activity information, were automatically removed by this technique as the density was too low to generate a temporal cluster (as explained in section 4.4.1).

This subsection presented the results of the KDE extraction of temporal clusters, the next subsection presents the results of the UMAP visualisations.

4.5.2 Analysis 2: UMAP Visualisations of the Temporal Clusters

This section presents the results of UMAP visualisations for objective 2 from Table 4.1, which was to visualise the extracted information to identify shifts in patterns of user activities. Figure 4.5 shows UMAP plots generated for each day of the week, for four 12-week periods (Period 1 (P1): weeks 2 to 14, Period 2 (P2): 3 to 15, Period 3 (P3): 4 to 16 and Period 4 (P4): weeks 17 to 29). Each data-point in the plot represents a temporal cluster which was extracted through KDE. As UMAP is primarily used for visualisation and clustering is generally not recommended (Wattenberg et al. 2017), the analysis included for this approach is therefore based only on what is visually discernible.

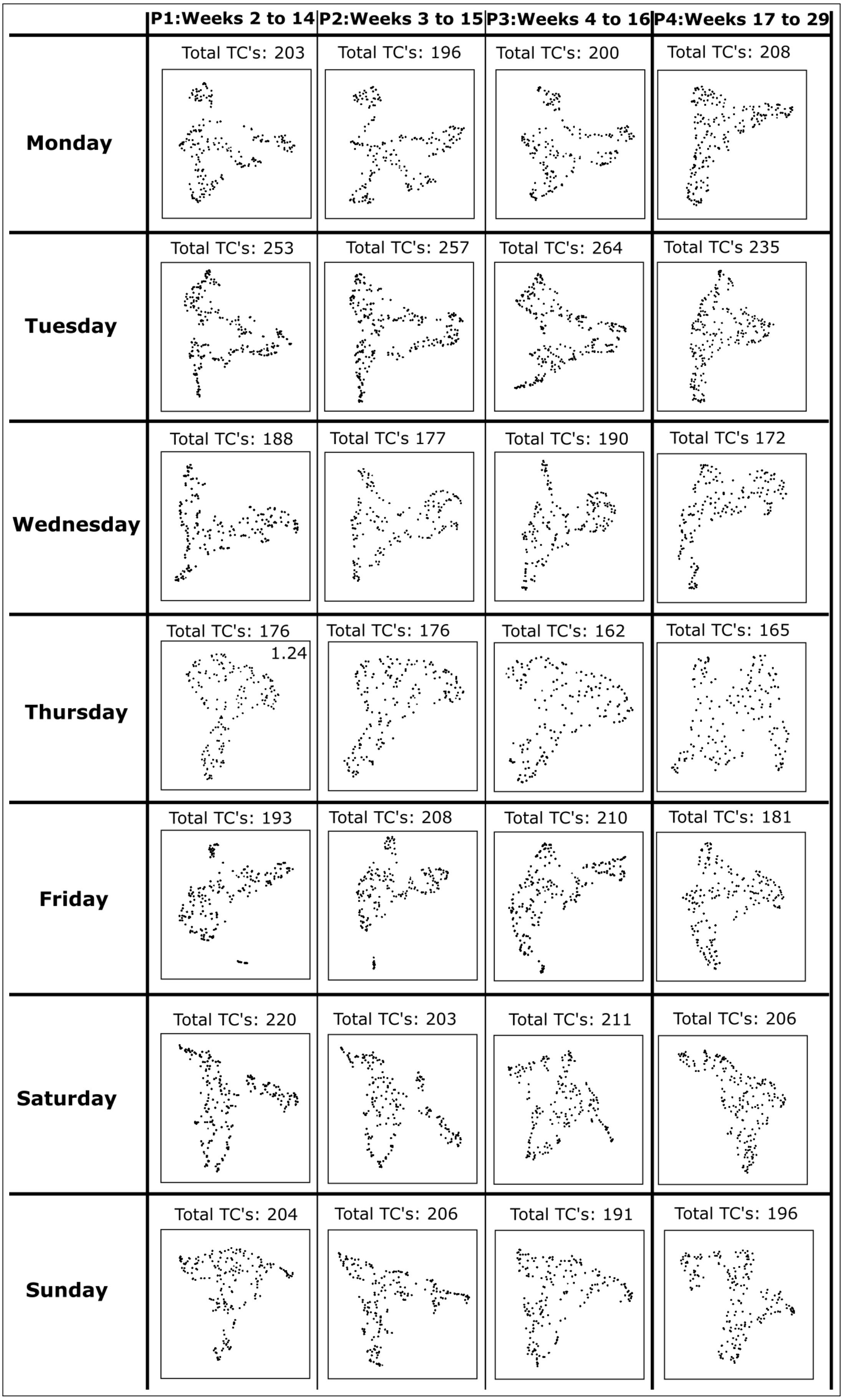

Figure 4.5: UMAP visualisations for each weekday for three overlapping 12-week periods, and one separate 12-week period. Total TC's – Total number of Temporal Clusters

As can be seen from Figure 4.5, the UMAP plot for each day of the week has a slight triangular morphology (most evident in Tuesdays). This morphology is a representation of the user's daily routine, with the indication of a triangular morphology being that the data points represent activities that are divergent in three directions (three different types of activities), hence, the data points are segmented out in three directions. The further that a data point is from another point, the more different the activities represented by the two points are. However, each day of the week still has a distinct visual morphology that persists for at least the first three overlapping 12-week periods. Additionally, it can be observed that plots for Period 4 (weeks 17 to 29) in Figure 4.5 are visually different compared to the plots for the preceding three periods, with the exception of Fridays. While we cannot conclusively determine the cause of this difference, noting of the presence of similarities and differences by the carer could be used as a mechanism to prompt further investigation through a discussion with the service user.

For Mondays, Figure 4.6 shows the UMAP changing over time from week 2 to 29. Each plot comprises data from a 12-week period, with a step-size of 3 weeks. There is a gradual, but visually discernible shift in the UMAP pattern over time.

When comparing the number of temporal clusters between the individual days of the weeks over all the four time periods, it can be seen in Figure 4.7 that the number of temporal clusters are lower on Wednesdays and Thursdays. As the number of temporal clusters are indicative of the overall level of activity, this indicates that the user is less active on those days. This information could provide useful insight for the carer as to the user's different activity levels over the weeks. Furthermore, in Figure 4.7 a trend of a reduced number of temporal clusters for Period 4 can be noted when compared to the previous periods 1, 2 and 3. This is particularly evident for Tuesdays and Fridays.

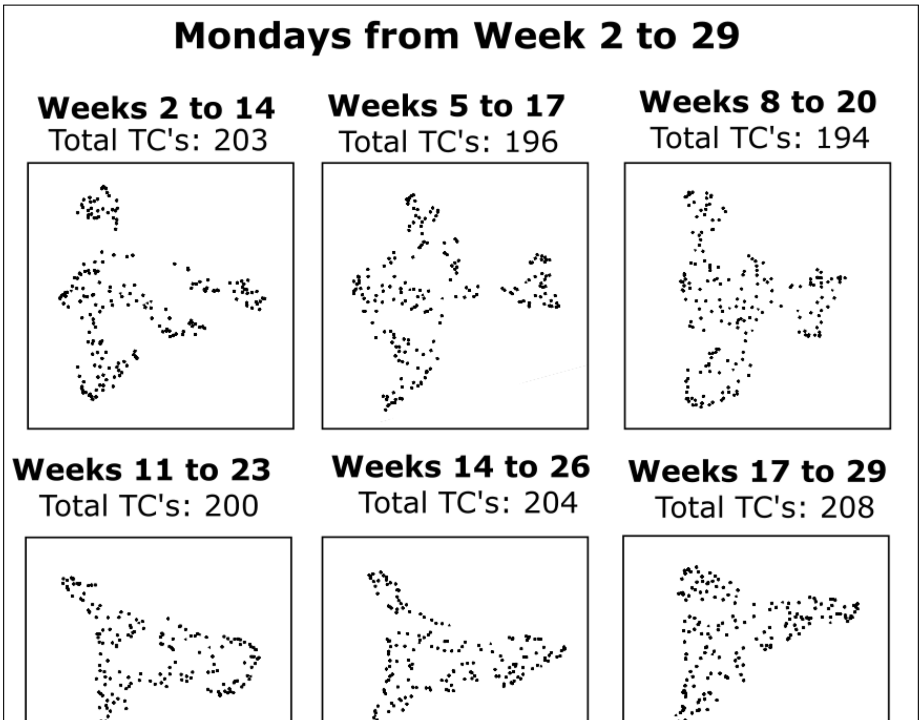

Figure 4.6: UMAP for Mondays for 12 week periods moving forward by 3 weeks at a time, from week 2 to 29

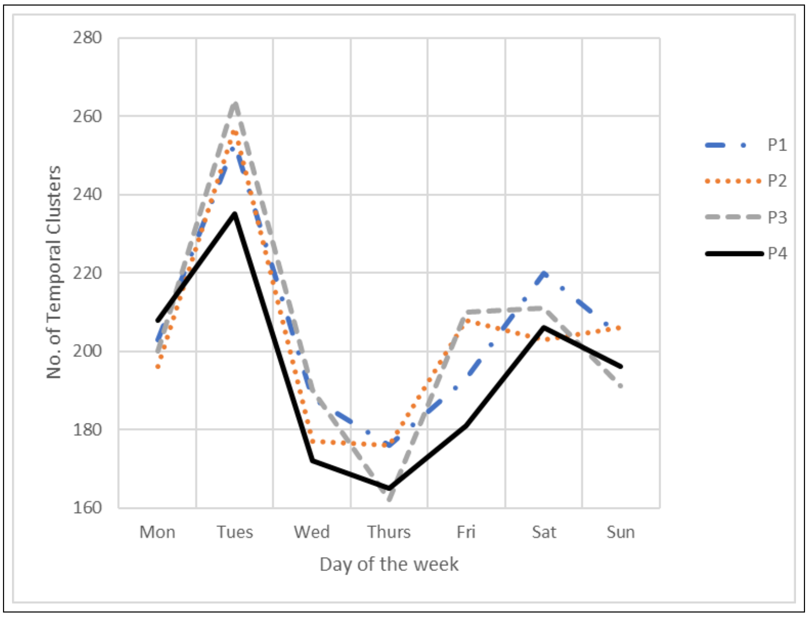

Figure 4.7: Graph comparing the number of temporal clusters between the four time periods (P1, P2, P3 and P4)

In Figure 4.5, it can be seen that in addition to the overall UMAP cluster morphology, the level of dispersion of the points is also different for different days of the week. For example, when comparing Mondays to Thursdays in Figure 4.5, a difference in the dispersion of points between Mondays and Thursday is visually discernible, i.e. the UMAP for Mondays has areas of varying density of points, while the UMAP for Thursdays is comprised of more uniformly distributed points. This could be partially explained by the lower number of temporal clusters present on Thursdays as shown in Figure 4.7, however, Thursday for P4 has more temporal clusters than P3 but the data points in the former are still more dispersed, with a less distinct morphology. To gain further insight into these differences, radar graphs were generated for Mondays and Thursdays to identify the total number of temporal clusters at different times of day (ToD), similar to the approach presented by Fiorini et al. (2017).

4.5.3 Radar Graph Comparison

The radar graphs presented in Figures 4.8 and 4.9 show the total number of temporal clusters at different times of day (ToD), and the standard deviation for each ToD over the 12-weeks. The activity, as represented by the number of temporal clusters at different ToD, in the radar graphs for P1, P2, and P3 are more similar to each other, while the radar graph for P4 shows different activity levels at different ToD for both Mondays and Thursdays. This correlates with the differences in the dispersion pattern of points in the UMAPs from Figure 4.5.

When comparing Mondays to Thursdays in Figure 4.8 and 4.9, Mondays indicate a more regular routine than Thursdays. This is also corroborated from the lower standard deviation for the majority of the ToD clusters for Mondays when compared to Thursdays. This relates to why the UMAP for Thursdays is more spread out and less distinct when compared to Mondays.

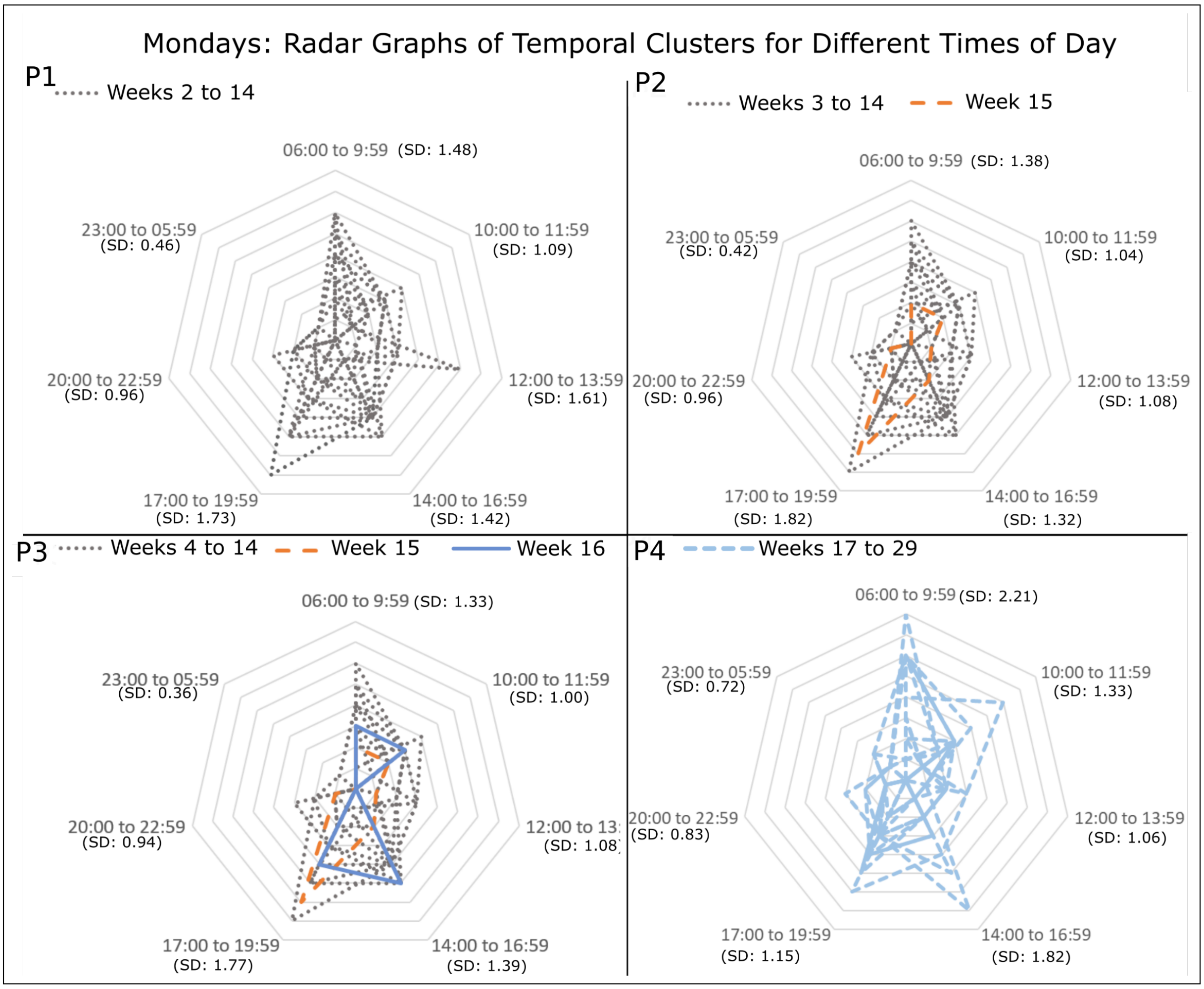

Figure 4.8: Mondays: Radar graph for each 12 week period showing the total number of Temporal Clusters at different times of day. SD = Standard Deviation in total number of Temporal Clusters for that time of day.

For both Mondays and Thursdays, the standard deviation for P4 is the highest (reaching a maximum of 2.21 and 2.13 respectively). The radar graphs show a more varying pattern of activity for different times of the day during P4 than during the previous periods P1, P2 and P3. The UMAPs for Thursday also indicate differences between the first three periods and P4. It should also be noted that as can be seen on the P4 radar graph for Thursdays, there are two ToD's with a standard deviation higher than 2, which could explain why the UMAP for Thursdays in P4 is much less distinct in terms of morphology and distribution.

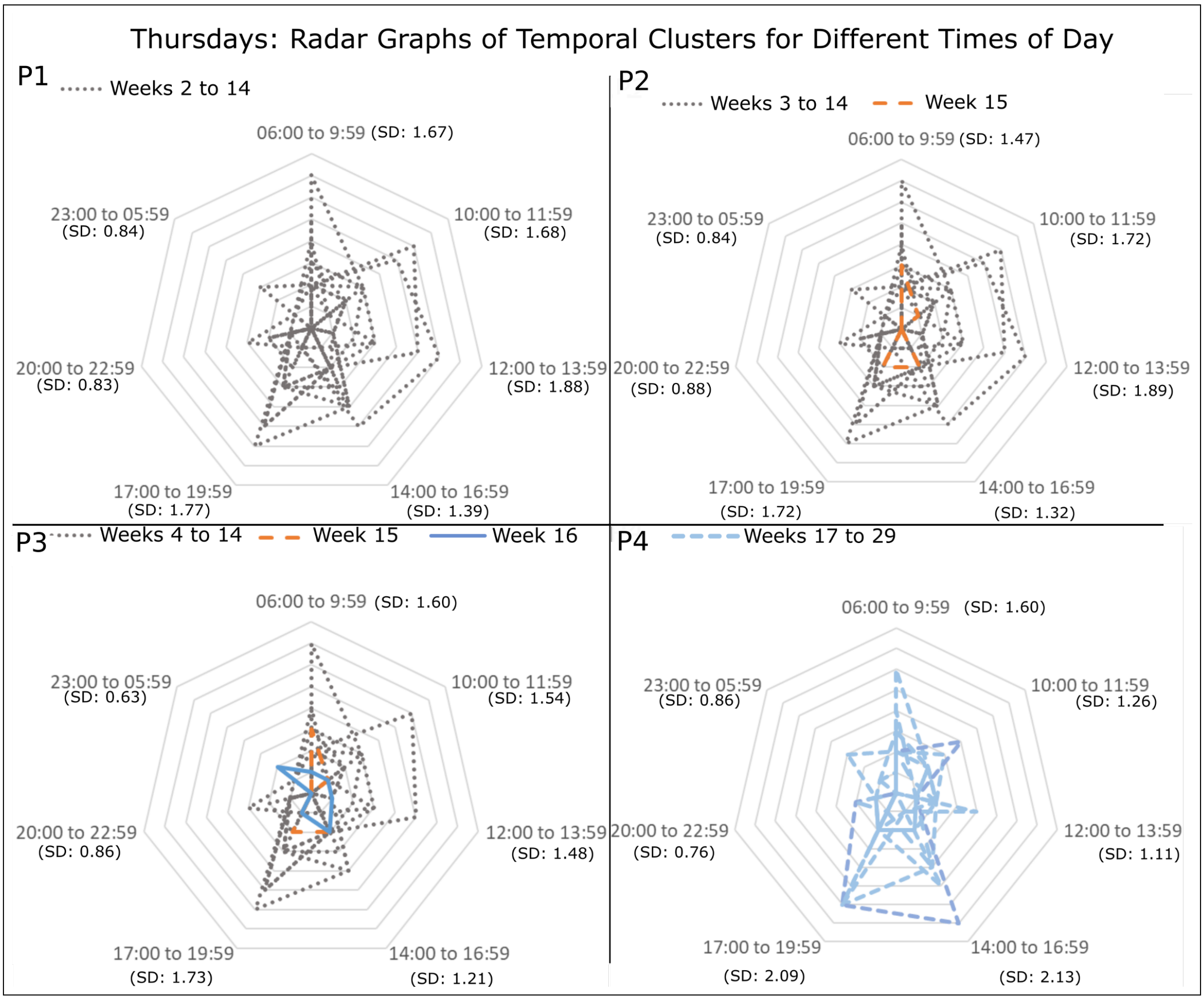

Figure 4.9: Thursdays: Radar graph for each 12 week period showing the total number of Temporal Clusters at different times of day. SD = Standard Deviation in total number of Temporal Clusters for that time of day.

This analysis goes some way in explaining how the UMAPs in Figure 4.5 encapsulate information about the regularity of a user's routine, as when the user has a more fixed and repeatable routine, the corresponding UMAPs show a more distinct morphology and dense dispersion pattern of points. It must however be noted that the UMAP encodes more information from the temporal clusters than the one parameter shown in the radar graphs, as the UMAPs are generated using the full feature set as presented in 4.2. Therefore, while the radar graphs show the total number of temporal clusters for each ToD, the morphology and dispersion density of points in the UMAP plots encapsulate much more information than just the temporal clusters. Visualising the activity data through UMAP is put forward as a visualisation technique which could enable carers to identify changes over time. It is envisaged that if a visually discernible change was noted, the next step would be for the carer to examine the specific activity data in more depth and initiate informed discussions with the service user to understand what may be causing these changes and suggest appropriate interventions if the change is detrimental to their well-being. For further objective analysis of the data, pattern recognition and blob analysis to automatically detect changes in the user's routine based on the changes in the morphology and density patterns of the UMAP plots could be carried out. This would allow the system to then automatically flag changes in the user's routines as well as notify the user and their carer.

4.6 Summary

The work presented in this chapter illustrates how unsupervised learning techniques can be used to discover activity patterns in unlabelled data from WSNs such as motion sensors. A key advantage of this methodology is that it does not require hand-tuning of parameters for the unsupervised learning methods. KDE is used for automatically extracting periods of dense sensor activity, as opposed to using of traditional fixed-length sliding time and sensor windows. The benefit of using KDE is that the parameters can be statistically derived from the data and the method is not reliant on a fixed time window set by the user. This helps us achieve objective 1 from Table 4.1.

As carers are already overworked and have limited time for each user, it is crucial that the time they spend with the service user is utilised efficiently. As explained in Chapter 3, an emerging requirement of care providers was for them to be able to spend more time on social interaction to focus on the service users' life skills. Data visualisation techniques which would help them monitor service users who are more independent were suggested as a way to support this, as they would not have to spend as much time questioning the service user about their activities. The work presented in this paper revealed through UMAP and KDE, that individual week-day data, considered over long periods, could contain unique features that can be used to infer user activity levels and track any changes over the long term. The information discovered through UMAP visualisations could be further utilised as part of a structured process or assessment protocol which helps to identify anomalies or changes in user activity. This could then be used for supporting carer–patient interactions, or even tracking the effectiveness of interventions and medication on the user's health condition as indicated by their activity or changes to routines over time. This section of the work helped achieve objective 2 which was to visualise the extracted information from the unlabelled SH sensor data to identify shifts in patterns of user activities (table 4.1).

A limitation of this work is that the subsequent visualisation process has not been directly tested with care providers, and therefore the real-world effectiveness of this solution cannot be verified. Future work suggested includes trialling UMAP and radar graph visualisations directly with carers and their service users. However, this work lies outside the scope of this PhD, and would therefore be investigated as a part of a separate study in the future. The goal of this work was to investigate the viability of unsupervised data extraction and visualisation techniques at identifying changes in the user's activity over time through the use of ambient SH sensors. Accordingly, this chapter presented a novel approach to generate insights on changing user activity over time from unlabelled data in an unsupervised manner. The next steps for this PhD will involve developing a real-time implementation using the KDE technique and tracking the kitchen activities in real-time. However, in order to do so, we first need to conduct our own data collection which is detailed in the next chapter.

Chapter 5

Experimental Design for Meal Preparation Data Collection

Chapter redacted for copyright reasons.

Chapter 6

Meal Preparation Dataset Analysis and Offline Learning

Chapter redacted for copyright reasons.

Chapter 7

Tracking Meal Preparation Activities in Real-time

Chapter redacted for copyright reasons.

Chapter 8

Discussion, Conclusions, and Future Work

The goal of this PhD was to investigate and develop intelligent data processing techniques utilising SH sensor data in order to support people with LD as well as their care providers. This Chapter summarises the findings of the research conducted in this PhD relating it to the existing literature, identifying limitations, and tying together the research findings in order to establish the overall contribution of this work.

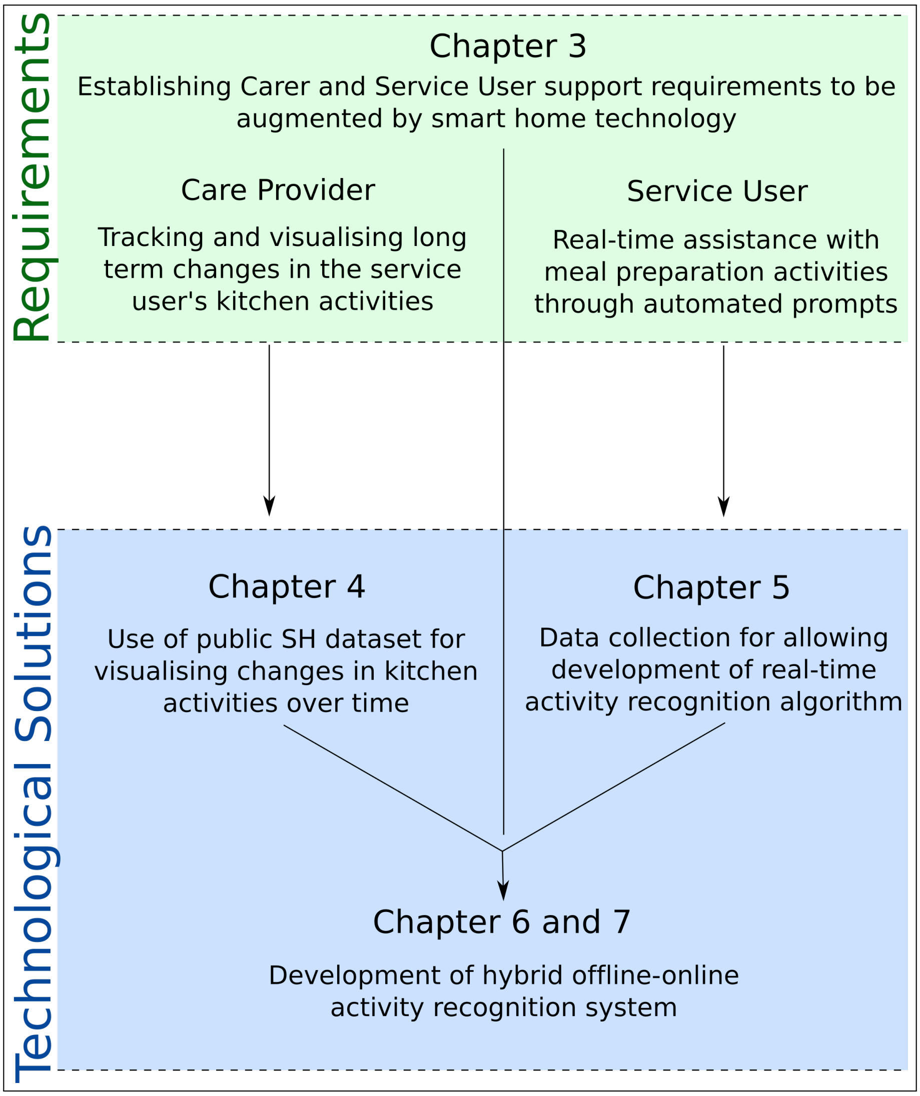

Figure 8.1: Research conducted in this PhD

The over-arching research question of this PhD was to investigate **How can SH technology be used to support people with LD to live more independently and receive more responsive care?** This research question was divided into two themes, establishing user requirements and developing the technological solutions. Figure 8.1 shows how each of the Chapter relates to these two themes, building from the findings of the first theme to undertake the technical development in the second theme.

The discussion begins with findings of this PhD for establishing the carer and service user requirements, then moves on to the technical development undertaken by the utilisation of a public SH dataset, following which a discussion on the development of the hybrid offline-online HAR using the SH sensor data collected is presented. This is then followed by a list of recommended future work to build upon the research presented in this PhD, before finally concluding with the overall contribution of this research.

8.1 Service User and Carer Support Requirements

The first phase of this PhD focused on establishing the carer and service user support requirements for answering the first two research questions of this PhD:

RQ1. What type of support is needed by people with LD in order to live more independently in the context of Ambient Assisted Living?

RQ2. How could SH sensing technology be best utilised to augment the support provided by care providers?

These research questions were answered through a combination of literature review and interviews conducted with care providers. The significance of the interviews in part had to do with the fact that this research was focused on people with LD. As iterated in the literature review, most existing research into AAL focuses on other vulnerable user groups such as older people with cognitive impairments and people with dementia. This is why it was crucial to conduct primary research with care service providers of people with LD in order to verify support requirements which are similar to other user groups and covered in existing literature, as well as identify requirements which are specific to this user group.

The interviews revealed that support with meal preparation activities was a universal requirement for people with LD who were a part of the care service. This would take the form of prompting the person in case they halt the activity as real-time support for the service user, as well as tracking their performance over time in order to determine any changes in their condition and tailor the care provision accordingly. Both of these were identified as potential areas of the care provision which could be augmented using SH technology through the research conducted in this PhD. Literature review had previously revealed that the target user group for this type of AAL technology can be divided into requirements of the care providers and requirements of the service users (Chapter 2.2.1). This was further validated through the findings of the interviews, as the interviewees indicated separate solution requirements for themselves, and their service users. In the case of kitchen activities, real-time support in the house was expressed as a requirement of the service users, while being able to visualise and track long-term changes in the service user's activities was stated as a requirement of the care providers to further tailor their service according to the user. This directed the technical work in this PhD to focus on utilising SH sensors for tracking meal preparation activities in order to provide automated prompts, as well as using long-term kitchen sensor data to visualise changes in how the person performs the activities over time. The interviews also helped with the selection of the SH sensors which could be used to achieve the said goals. The feedback received on the sensors also further validated the findings from the literature review as expanded upon in Chapter 2.3. In addition, the interviews also indicated the need for deploying the solution in such a way as to provide the service users control over the sensors, specifically the ability to switch the system off when desired. Findings such as these ones add to the growing requirements of care providers and service users in existing literature, while also identifying the requirements unique to people with LD. A broader context is provided in Chapter 3 detailing the carer profile and requirements, service user profile and requirements, and emerging design requirements for future AAL technology. This would in-turn enable future technology developers for people with LD to take into account the support requirements of both the care providers as well as their service users, utilise the profiles for understanding the diversity of user needs, as well as gain insights into potential barriers for the adoption of the technology due to factors such as familiarity of the users with technology and concerns about the use of SH sensors.

8.1.1 Limitations

The key limitation of this investigation was that only a single care service organisation was used for the interviews, and it was suggested that future work can build upon the findings of the interviews in order to conduct a broader investigation with care organisation at more locations. The understanding of these care requirements helped answer RQ1 and RQ2 which in turn dictated the direction of the technical development which was undertaken in this PhD, starting from the use of a public SH dataset to visualise changes in the user's daily routines as described in the next section.

8.2 Temporal Cluster Extraction and Visualisation using Public SH Dataset

Following the establishment of carer and service user support requirements, the next phase of this PhD focused on the development of technological solutions to augment the care provision. The first part of this work focused on RQ3:

RQ3. How can SH sensor data be utilised for informing care providers about changes to the service user's kitchen activities?

A public SH dataset was used in order to investigate the utility of SH sensors for visualising changes in a person's activities over time. As described in Chapter 4, the Aruba CASAS dataset was selected which contained data from a set of motion sensors installed in a person's house. This work utilised Kernel Density Estimation (KDE) and introduced the concept of temporal clusters for extracting sequences of sensor events that could represent user activity from the sensor data. The temporal clusters were then visualised through Uniform Manifold Approximation and Projection (UMAP) to reveal patterns in the user's routines based on day of the week.

The main significance of this investigation was two-part; firstly, that temporal clusters could extract activity information from SH sensors such as motion sensors which represent user activities, verified through checking whether the activity labels present in the dataset were extracted successfully using this method. Secondly, that these temporal clusters could be utilised for visualising and revealing patterns in the person's kitchen routine. As this type of analysis had not been conducted previously in existing literature, it had been unclear whether the sensor data would contain too much noise and randomness to detect such patterns. The use of temporal clusters along with UMAP provided a methodology for filtering out noise and visualising changes in user activities.

The implication of these findings was that visualisation tools based on the methodology presented could be utilised by care service providers for tracking kitchen activities of the service users and pick up on changes in their routines based solely on motion sensor data. This in turn could be utilised for tracking the effectiveness of interventions and medication on the user's health condition based on changes in their activity performance. This work helped towards answering RQ3 and showed how temporal clusters can be utilised for extracting actionable information from the SH sensor data.

8.2.1 Limitations

While the evaluation of this work was based on the consistency of the generated visualisations in order to infer changes in the user's routine, they were not directly tested with people with LD and their care providers to determine their real-world effectiveness which should be investigated as a separate research project in the future. Additionally, a drawback of using the public SH dataset was that a more detailed analysis of the user activities, specifically for tracking them in real-time, could not be conducted due to the lack of contextual information present in the data labels as well as the data being limited to only motion sensors.

8.3 Real-World Sensor Data Collection and Integration of Offline - Online HAR

The next phase of the technological development focused on RQ4:

RQ4. How can real-time support for meal preparation activities be enabled by the use of SH technology?

Answering this research question included conducting SH sensor data collection using more sensors than the public SH dataset as well as recording more contextual information for data labelling. This was done to enable the development of HAR techniques for real-time tracking of the meal preparation activities. The methodology followed for this data collection is detailed in Chapter 5.

This data collected was also a major contribution of this research, as it was unique from existing publicly available datasets due to the higher granularity of labels provided and the combination of ambient sensors and thermal cameras used. This data would allow researchers to develop and verify results of HAR techniques for distinguishing between different types of meal preparation activities, different participants performing the same type of meal preparation activity, as well as tracking the activity step-by-step which was not possible before from available datasets. The dataset was also unique as it combined ambient sensors in the environment of the user along with two low-resolution thermal cameras, whereas most public datasets focus on a single type of sensor setup.

The goal of the technical work that followed the data collection was to develop a methodology for utilising the SH sensor data for tracking meal preparation activities in real-time. Most existing research into HAR focuses on utilising supervised learning methods for categorising/classifying activities (Vrigkas et al. 2015, Wang et al. 2019), as opposed to tracking them in real-time. The offline-online HAR methodology presented in this PhD provides a unique semi-supervised approach by learning the activity models from previous sessions in order to track them in real-time. Offline HAR was utilised for analysing the historical data which combined WSN and thermal camera data in order to build a temporal cluster database. This database was in turn utilised for performing online HAR in order to track the meal preparation activity in real-time. This resulted in a system that learnt incrementally and therefore did not require expertly supervised training, making the system more practical for real-world deployment.

Furthermore, it was also demonstrated how this methodology could be utilised to track and investigate deviations from the activity, which is not only instrumental for the development of real-time intervention tools, but also visualisation tools for facilitating informed discussions between care providers and their service users. Interventions arising from real-time tracking of activities can help the user in performing the activities more independently, reducing the hours of care required. This would in turn enable the carers to spend more time with the user for interacting socially as was expressed through the interviews conducted in Chapter 3. This interaction is further aided by the reporting of deviations by the HAR system. Therefore, the technological solutions presented in this thesis for tracking long-term changes in kitchen activities as well as tracking meal-preparation activities in real-time, were able to address the over-arching research question by demonstrating how SH sensor data can be utilised for developing technologies to support people with LD in living more independently as well as receiving more responsive care.

8.3.1 Limitations

The key limitation of this technical work include that it has only been tested on a dataset derived from a single kitchen, with three participants, and three meal preparation activities. Future research must be conducted to verify how well the presented methodology works for different kitchen layouts, participants, and more types of meal preparation activities. Furthermore, the HAR system presented in this PhD only utilised the top view thermal camera for tracking the participant position, it is also recommended for future studies to investigate the use of the side-view camera for further improving upon the system. Further recommendations are made throughout the thesis where future work may be carried out to further build upon the presented HAR system. This includes development of an interface for user interaction, automated parameter selection methods for the online HAR system, and testing of deviation tracking with real-world service users.

8.4 Future Work

This sub-section presents a list of recommended future works to be carried out which build upon the research in this PhD:

- It is highly recommended to expand upon and further validate the findings presented in Chapter 3 by conducting a larger stakeholder engagement study with care providers as well as their service users. The research in this PhD only focused on care providers from a single organisation, therefore, future work must be conducted to compare experiences of care staff at different organisations. Direct engagement with service users is also necessary as they, along with the care provider, are identified as the end-users of the AAL system.
- It is also crucial to use the technical development carried out in Chapter 4 to build more visualisation tools and test them directly with care providers as well as their service users. Specifically, the use of exploratory unsupervised classification techniques which could work in conjunction with t-SNE must be investigated. It is also crucial to gain an understanding into the usability of generated visualisations from the care provider's perspective, and explore whether similar visualisations can be utilised by service users to live more independently. Another form of visualisation, which has not been investigated in this PhD, could explore the use of thermal camera data from the meal preparation dataset that was collected as a part of this research. Specifically, the heatmaps generated from the thermal

cameras could be investigated for presenting snapshots of kitchen activities to care providers.

- While the research in this PhD focused on developing a hybrid offline-online HAR model, the meal preparation dataset collected as a part of this PhD should be utilised for investigating other types of HAR techniques as well. Supervised and knowledge-driven HAR techniques (such as those which utilise the concept of transfer learning) should be investigated using this dataset. This is because knowledge-driven models can especially benefit from the detailed labelling and contextual data labels that are present in the dataset.
- Furthermore, the HAR technique developed in this PhD only utilises the top view thermal camera for extracting the movement trajectory of the participant as they prepare the meal. However, no other feature from the camera is extracted, including the side-view thermal camera which could be further used for pose-recognition. Thermal analysis and image recognition machine learning methods should be investigated for performing real-time HAR using data from both the thermal cameras.
- The dataset captured includes meal preparation, meal consumption (which multiple individuals present at the same time), and washing-up afterwards. While the focus of this PhD was purely on recognising meal preparation, recognition of meal consumption is also an important area which must be investigated. This would be particularly useful for allowing care-providers to track eating habits of their service users which may be impacted by health issues or change in medications.
- With regards to the offline-online HAR system presented in this PhD, the primary focus of future work should be on the deviation detection and prompting aspects of the system. Specifically, as described in sub-section 7.3.4, the suggested threshold parameters for detecting deviations must be investigated. This is the most crucial aspect of the HAR system as it is needed to alert care providers as well as enable prompting to support service users.
- Building upon this deviation detection, automated prompting techniques also need to be investigated. This prompting will be dependent on the recognition of the first two types of deviations (as outlined in sub-section 7.3.4) but is crucial for enabling service-users to perform activities more independently.
- Lastly, user-interaction would play a large role for the HAR system proposed in this PhD to work in the real-world. This includes receiving information from the participant and their care provider as outlined in the previous chapter, as well as providing the necessary prompts. This user-interaction element was left out of the research conducted in this PhD but is a necessary requirement for the system to be practical for the real-world. This user interaction system can range from a simple tablet screen to more elaborate social robots, and investigating this element would form a significant piece of research by itself.

8.5 Conclusions

The over-arching research question of this PhD was How can SH technology be used to support people with LD to live more independently and receive more responsive care, which was answered by first engaging with domain experts in order to establish support requirements, and then by undertaking technical developments aimed at fulfilling those requirements.

Accordingly, the overall contribution of the research conducted in this PhD was in two areas. The first main contribution was towards the understanding of support requirements for people with LD and their care providers. The research conducted in this PhD lead to a synthesis of carer and service user profiles, as well as emerging design requirements for future AAL technology. The research also highlighted support requirements that can be assisted through technology which are specific to people with LD, and have been missing from existing literature. This work can be utilised by service providers for selecting appropriate SH technology to be used with service users as well as future assistive technology developers. This work also provides the foundation for future researchers engaging directly with people with LD to build upon.

The second area of contribution of this PhD was towards the field of HAR. This includes the meal preparation data collected as part of this PhD, which is unique in terms of the variety of sensors used and the contextual data labels provided. The latter allows the development of more knowledge-driven HAR techniques which are aimed at tracking an activity step-by-step, as opposed to classification/categorisation of activities which dominates existing HAR literature (Vrigkas et al. 2015, Wang et al. 2019). This PhD also further built upon the field of unsupervised and semi-supervised methods for performing both offline and online HAR in order to track activities in real-time. The utilisation of an offline-online HAR methodology provided a way to learn meal preparation activities automatically from the user, negating the requirement of labelling large amounts of data for training.

This technical work provides a foundation on which not only can intervention tools be built upon for supporting people with LD in performing meal preparation activities, but also visualisation tools be developed for facilitating informed discussions between the care provider and the service user. Both of which were demonstrated in this PhD using SH sensor datasets.

The main limitation of this work was that the technical developments presented in this PhD were not tested with the target user group of people with LD and their care providers. This means that claims could not be made regarding the real-world effectiveness of the solutions presented in Chapter 4, 6, and 7 for supporting people with LD. Instead, the focus of this work was on developing solutions according to the requirements established in Chapter 3, and evaluating the results of the HAR systems based on their accuracy. As demonstrated in Chapter 7, the presented methodology can be expanded upon for tracking deviations in order to develop automated interventions. It is recommended that any interventive technologies built using the methodology presented in this thesis be tested with service users in order to determine the real-world effectiveness of the solutions.

Research in the field of HAR has shown promising results but the resultant solutions still have various barriers to adoption, which includes the amount of training data required by the supervised machine learning algorithms. The research presented in this thesis takes a critical step towards making HAR more practical, from the types of sensors utilised to the semi-supervised nature of the approach which aims at learning from the user over time. However, as evident from the limitations listed in this chapter, this research is only a piece of the puzzle that aims to enable the development of interventive and analytical tools for supporting people with LD in performing activities more independently, as well as reducing the work-load of the care staff by utilising their time more effectively. As ongoing research in this field advances, the future of such ambient assistive technology looks bright, bringing together different elements that form an ecosystem of smart IoT technology, assistive robotics, and care service integration enabling a new vision for independent living.

Publications

The research conducted in this PhD also lead to the following publications:

Gupta, P., McClatchey, R. and Caleb-Solly, P., 2021. Intelligent IoT Systems to Support Self-Management – Requirements for People with Learning Disabilities and their Care Providers. *In 17th International Conference on Intelligent Environments*

Contributions: RM and PCS contributed to the conception of the study and the design of the methodology. PCS selected the regional care provider and helped organise the interviews. The actual interviews and the analysis were conducted by PG with direct input from PCS. The initial draft was completed by PG with guidance from RM and PCS. All authors contributed to manuscript revision, read and approved the submitted version.

Gupta, P., McClatchey, R. and Caleb-Solly, P., 2020. Tracking changes in user activity from unlabelled smart home sensor data using unsupervised learning methods. *Journal of Neural Computing and Applications*, pp.1-12.

Contributions: RM and PCS contributed to the conception of the study. PCS provided technical input to PG regarding the data analysis while RM provided feedback on the writing and formatting of the paper. PG conducted the public dataset search and selected the final dataset, as well as performed the actual data analysis. PG completed the first draft with support from RM and PCS. All authors contributed to manuscript revision, read and approved the submitted version

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Appendices

Appendix A

Supplementary Tables and Figures

Appendix redacted for copyright reasons.

Appendix B

Ethics Applications

Appendix redacted to protect personal information.

Appendix C

Publications

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Tracking changes in user activity from unlabelled smart home sensor data using unsupervised learning methods

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Abstract

This paper investigates the utility of unsupervised machine learning and data visualisation for tracking changes in user activity over time. This is done through analysing unlabelled data generated from passive and ambient smart home sensors, such as motion sensors, which are considered less intrusive than video cameras or wearables. The challenge in using unlabelled passive and ambient sensors data for activity recognition is to find practical methods that can provide meaningful information to support timely interventions based on changing user needs, without the overhead of having to label the data over long periods of time. The paper addresses this challenge to discover patterns in unlabelled sensor data using kernel density estimation (KDE) for pre-processing the data, together with t-distributed stochastic neighbour embedding and uniform manifold approximation and projection for visualising changes. The methodology is developed and tested on the Aruba CASAS smart home dataset and focusses on discovering and tracking changes in kitchen-based activities. The traditional approach of using sliding windows to segment the data requires a priori knowledge of the temporal characteristics of activities being identified. In this paper, we show how an adaptive approach for segmentation, KDE, is a suitable alternative for identifying temporal clusters of sensor events from unlabelled data that can represent an activity. The ability to visualise different recurring patterns of activity and changes to these over time is illustrated by mapping the data for separate days of the week. The paper then demonstrates how this can be used to track patterns over longer timeframes which could be used to help highlight differences in the user's day-to-day behaviour. By presenting the data in a format that can be visually reviewed for temporal changes in activity over varying periods of time from unlabelled sensor data, opens up the opportunity for carers to then initiate further enquiry if variations to previous patterns are noted. This is seen as an accessible first step to enable carers to initiate informed discussions with the service user to understand what may be causing these changes and suggest appropriate interventions if the change is found to be detrimental to their well-being.

Keywords Human activity recognition · Unlabelled sensor data · Data visualisation · Unsupervised learning

1 Introduction

With a growing shortage of carers and an ageing population, there is an urgent need to explore how smart sensing technologies could be utilised to support and maintain a high quality of agile and responsive care. Accordingly, researchers have been developing ambient assisted living (AAL) technology which utilises data from a range of smart home (SH) sensors to support people with long-term conditions to live independently [1]. The kitchen is usually the centre of user activity, particularly for those who are still managing to live independently. Additionally, most frequently occurring household injuries for vulnerable people occur in the kitchen, which can lead to loss of confidence in performing kitchen activities over time and moving to a nursing home [2, 3]. As such, tracking activities in the kitchen over time can provide the requisite baseline data for identifying early indicators of changes which might require interventions. Early intervention can

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prevent, and pre-empt, more serious issues from happening in the future.

A large area of AAL research is focussed on performing human activity recognition (HAR) from SH sensor data. This includes detecting activities offline, after they are finished, as well as detecting activities in real time as they occur. Real-time HAR is essential for interventions such as assistive prompts, while offline HAR is useful for tracking changes in user behaviour over time, detecting abnormal behaviour, as well as performing wellness evaluations.

The SH sensors used for HAR can be broadly categorised into wireless sensor networks (WSNs), body sensor networks (BSNs) and video-based solutions. WSNs comprise sensors that are integrated into the environment of the user such as passive infrared (PIR) motion sensors, magnetic contact sensors, and temperature sensors. Generally, a large number of WSNs are required to be present in order to perform HAR [4]. BSNs comprise sensors which can be present on the user, such as wearables which can provide accelerometer and GPS data along with the users' physiological information. Although the data provided by BSNs can be crucial for performing HAR, end-users can often forget to wear the sensors or charge them, or consider them intrusive. Video-based solutions provide the most context on the user and can range from RGB-D data to thermal imaging; however, they are generally considered an invasion of privacy by end-users [5, 6]. As cost-effective WSNs are becoming more commonly available as consumer products and are considered more acceptable than video-based solutions, exploring and developing their utility as part of an effective AAL technology solution to support users for living independently is a crucial next step.

There is a variety of existing research into HAR which has utilised supervised learning techniques using WSNs, BSNs, as well as video-based solutions with promising results. The problem with supervised learning is that it requires large amounts of user-annotated or labelled sensor data for training. This is often difficult to obtain for each individual user the system needs to be deployed for, and the subsequent trained classifier is also unable to adapt to changes in user behaviour without re-training with more labelled data. A common approach when collecting data for training classifiers requires the user to self-report or log activities through a diary, which is then used to annotate the data [7]. This introduces issues related to the reliability of the labels, as the user may forget to label every activity he/she performs or may not provide sufficient detail describing the activity [7]. This is evident in many user-annotated public smart home datasets where a simple "meal preparation" label is provided that can encompass a range of different types of cooking activities. Lastly, self-reporting of activities can be a tiring and tedious task, particularly when required to be conducted over many weeks or months and may not be possible for end-users with cognitive impairments. As such, researchers in this field are also investigating the use of unsupervised learning techniques, with a view to eliminating the need for labelling SH data. However, most of the existing research studies that have shown promising results used context-rich information obtained from BSNs and video-based solutions, and not WSNs. Researchers such as Fiorini et al. [8] used unsupervised learning with WSNs; however, in this case the authors were looking for an overall user "busyness" metric rather than individual user activity patterns.

This paper presents a novel approach for analysing unlabelled smart home sensor data, focussed on discovering patterns in user activity by analysing each of the days of the week separately over three 12-week periods. The approach presented in this paper is developed and tested on a total of 203 days of data from the kitchen-based sensors in the Aruba CASAS dataset [9]. By disregarding any labels present in the dataset for the visualisation, we seek to identify and understand sub-patterns that might exist with a view to interpreting user activity over time. The scope of this paper is to be able to inform the process of inquiry by the care provider for early intervention if variations to previous patterns are noted. This is seen as an accessible first step to enable carers to initiate informed discussions with the service user to understand what may be causing these changes and suggest appropriate interventions if the change is detrimental to their well-being.

The rest of the paper is structured as follows, Sect. 2 reviews existing HAR and data mining techniques in more detail; Sect. 3 provides a description of the Aruba CASAS dataset as used in the study; Sect. 4 describes the methodology, the data pre-processing and feature selection, and data visualisation techniques for discovering user activity patterns; Sect. 5 presents the results and discussion; and finally Sect. 6 summarises the conclusions and discusses future work.

2 Background and prior work

This section reviews HAR techniques in more detail, while also reviewing data mining techniques which have been used for applications other than HAR, utilising unsupervised learning.

In order to perform HAR, periods of sensor data events that may represent activities must be extracted first. Traditional approaches for this include the use of sliding time and sensor windows as used by Yala et al., Cook and Krishnan [7, 8]. These sliding windows are generally used for training supervised learning systems when activity labels are present, as the sliding windows can be chosen based on the activity labels present in the data, and windows containing noise can be removed manually. However, due to this, they are not as well suited for unlabelled data as it would be difficult to identify windows that contain noise. The lengths of these windows are also often fixed which makes the activity recognition system highly sensitive to variance in the distribution of sensor events throughout the day. Therefore, it is important to investigate alternative approaches for extracting periods of sensor data events of variable lengths.

An alternative approach is presented by Soulas et al. [6] for discovering "episodes" of user activities along with their periodicity and variability. The authors use an episode length of 30 min which essentially acts as a time window for extracting sensor data which may belong to an episode. However, this is left as a parameter to be set by the user depending on their daily habits. Along with this, Soulas et al. also define five additional parameters which need to be set by the user and the user's physician in order for the algorithm to work. The authors acknowledge that setting unsuitable parameters can lead to missing interesting information and other automated candidate episode generation techniques need to be investigated. Nevertheless, the paper highlights the need for HAR algorithms that do not require priori knowledge on the user. They also provide an analysis into the variability and repeatability of user behaviour present in the public SH datasets; however, their approach for this requires considerable hand-tuning of the learning methods.

In the work presented by Gupta and Caleb-Solly [10], sensor data was analysed by room only, and treated as 1D time series data per room, only comprising of sensor event timestamps. An alternative approach to sliding windows in this case would be to find and extract periods of high-density present in the sensor data which could potentially represent activities. As the sensor data can be treated as 1D time series, kernel density estimation (KDE), as first proposed by Rosenblatt, can be a powerful tool for extracting periods of sensor events which can potentially represent an activity [11]. KDE is a nonparametric method for estimating the probability density function of a random variable, and as such can be used to detect time periods of high-density present in 1D data. This overcomes the issue of deciding the size of sliding windows and has the added benefit of identifying only high periods of sensor activity and disregarding the rest as noise. KDE has two parameters—kernel function and the bandwidth. The kernel function must be chosen based on the properties of the data, while the bandwidth can be selected using Silverman's rule [12]. As these parameters can be derived statistically, KDE can be a potential alternative to traditional fixed-size sliding windows for extracting sensor data.

Once periods of sensor data are extracted, the next step is visualising the data. In recent years, new visualisation techniques have been introduced which have superseded existing techniques such as Self-Organising Maps (SOM's) and principal component analysis (PCA) in certain applications. These visualisation techniques include t-distributed stochastic neighbour embedding (t-SNE) [13] and uniform manifold approximation and projection (UMAP) [14], both of which are nonlinear dimensionality reduction techniques. T-SNE has often been the primary choice for researchers for visualising high-dimensional data in 2D and is noted for preserving the local structure of the data. UMAP on the other hand is a much newer technique and is capable of preserving both local and global structure of the data [15]. These techniques are particularly relevant when dealing with unlabelled data, as they can help to discover whether there are any meaningful features and potential clusters present. However, it must be noted that even though both t-SNE and UMAP are both useful choices for visualisation, clustering based on their output is generally not recommended, as density information is often lost during the process [16]. A useful technique is also presented by Fiorini et al. [8], where radar graphs were constructed from motion sensor data which can be used to facilitate a quick visual review of the sensor data. This technique can be used in conjunction with other visualisation techniques such as UMAP, to gain further insight into the sensor data.

To summarise, in this section the potential benefits of KDEs to replace sliding windows for extracting sensor data and the use of t-SNE/UMAP for visualising unlabelled data are highlighted.

The next section provides a description of the Aruba CASAS smart home dataset, which will be used for developing, as well as testing the unsupervised learning methodology presented in this paper.

3 Selection and description of the public smart home dataset

This section provides details of the selection process for the smart home dataset, and activities which were selected for use in this study. For this research, we focussed on the Washington State University's Centre for Advanced Studies in Adaptive Systems (CASAS) [9] dataset collection. This collection comprises a range of labelled, partly labelled, or unlabelled activity data, collected over varying time periods. The activities in these datasets are scripted or unscripted. The work presented in this paper is focussed on unscripted "daily life" datasets. Additionally, datasets which use BSNs or video cameras were not considered as the focus in this research is on utilising less intrusive WSNs, such as PIR motion sensors. Five public datasets met these criteria.

A further search was conducted for these five CASAS datasets on IEEE[1] with keywords ((((Smarthome) OR smart-home) AND '*nameofdataset*') AND CASAS). This revealed the Aruba dataset as the most frequently used dataset with 31 search results, and Milan as the second most frequently used with 15 search results. Based on this, both Milan and Aruba were shortlisted. The Aruba dataset has a total of 220 days of continuous data, while the Milan dataset has a total of 72 days of data. However, Milan is missing 11 days of data, while the Aruba dataset has continuous data with no missing days. The missing days could affect the performance of the HAR algorithm as it is crucial to analyse consecutive days in order to pick up repeating activity patterns. The Aruba dataset was therefore selected for developing and testing the unsupervised learning techniques presented in this paper.

The Aruba dataset consists of data from a total of thirty-nine sensors, out of which thirty-four are PIR sensors and five are temperature sensors. In this paper, only the PIR sensor data, which represent the occupant's physical movement in the vicinity of the sensor, is analysed. Therefore, after excluding temperature sensor data over the period of 220 days, a total of 1,602,980 sensor events are present out of which 849,579 sensor events ($\approx$ 53%) are not annotated with any activity labels in the dataset. Previous studies have often discarded these unlabelled sensor events when performing HAR as activities detected using the unlabelled data cannot be verified [17].

There are a total of 11 activity labels present in the Aruba dataset (Fig. 1). The primary kitchen activity labels are "Meal_Preparation" and "Wash_Dishes. There are a total of 1606 instances of the "Meal_Preparation" activity and only 65 instances of the "Wash_Dishes" activity. In previous studies, this imbalance has caused classifiers to misclassify the "Wash_Dishes" as "Meal_Preparation" activity [10].

As this study is focused on kitchen activities, only kitchen sensor data was analysed, which includes "Meal_Preparation" and "Wash_Dishes" activity labels. These event data represented by these two labels was further analysed to verify which sensors were associated with these labels in the Aruba dataset. Both "Meal_Preparation" and "Wash_Dishes" labels were primarily based on only kitchen sensors (five PIR sensors) being triggered over the entirety of the dataset; all other sensors in the house were associated with less than 5% of both the activity labels. This supports the approach previously presented by Gupta and Caleb-Solly [10], in which only kitchen sensor data was analysed when performing HAR for kitchen activities, considerably reducing the noise and amount of the data required to be processed. It should be noted that no unlabelled sensor data was removed by hand, as it was left to the unsupervised machine learning techniques to identify noise. As stated previously, this is different to previous studies by other researchers using this dataset, who removed all unlabelled data from the analysis as the activity represented by that data could not be verified [17]. The approach of retaining unlabelled data better reflects a real-world scenario, where a dataset is likely to contain unlabelled instances.

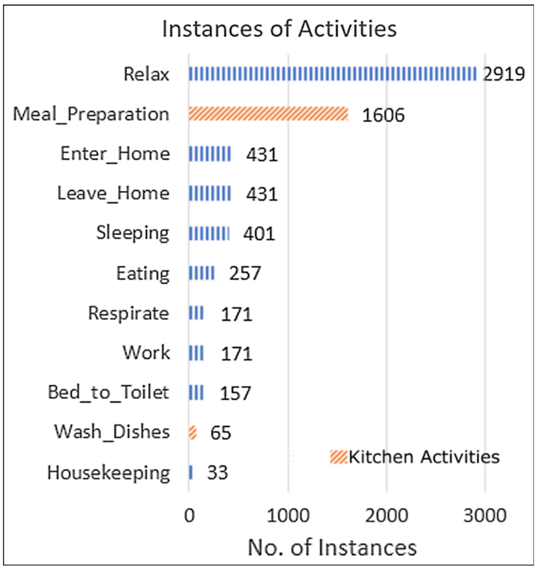

Fig. 1 Total instances of activity labels in the Aruba dataset

4 Methodology

This section outlines the methodology followed in this paper which includes extracting temporal clusters using kernel density estimation from sensor data, feature selection, and the use of data visualisation techniques.

All the algorithms were written in Python using various machine learning libraries which are referenced throughout the paper.

4.1 Extracting temporal clusters of sensor events using KDE

Over the past decade, as research into AAL and SHs has grown, various new concepts and terminology have been introduced to the field. In this paper, some of these existing concepts have been further developed, such as that of a temporal cluster. This study presents a method for extracting periods of high-density present in the temporal sensor data, which have been defined as temporal clusters (Fig. 2). Therefore, a temporal cluster ($\boldsymbol{TC_i}$) is a set of

[1] https://ieeexplore.ieee.org/.

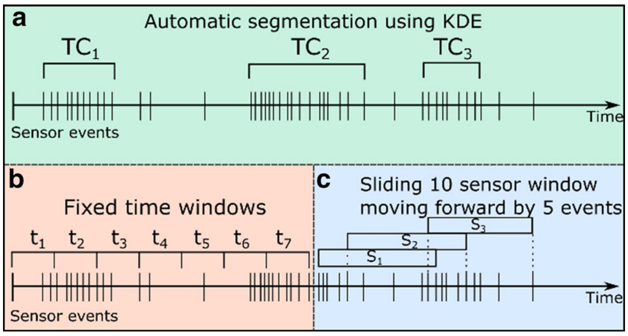

Fig. 2 **a** Sensor segmentation using KDE to extract temporal clusters (TC_i), **b** fixed time windows (t_i), and **c** sliding sensor windows with a length of 10 sensor events and sliding forward by 5 sensor events (s_i)

sensor events occurring close together $\{s_1, s_2, s_3, \ldots s_n\}$ that could potentially represent an activity.

In this study, temporal clusters are used with a view to identify activity patterns which might not have been represented by the user labels, but might still represent specific user activities or behaviour.

For developing this temporal cluster extraction approach using KDE, the Aruba dataset was divided into a training and test set. Days 10 to 42 were used as the training set and days 53 to 81 were used as the test set.

KDE requires the selection of a kernel and the kernel's bandwidth. After analysing the training set, the Epanechnikov kernel [18] was empirically selected for the algorithm. The Silverman's rule [12] for automatically selecting the bandwidth was also empirically adjusted to:

$$bw = 0.07\hat{\sigma}n^{-1/5}$$

where $\hat{\sigma}$ is the standard deviation of the sample, n is the sample size and bw is the bandwidth. The KDE temporal cluster extraction technique is illustrated in Fig. 3. This figure shows an example of KDE temporal cluster extraction process for the morning hours of 8 am to 10 am for a selected day from the Aruba dataset. For the experiment, KDE was used to generate a density curve for the whole day which was then used to extract temporal clusters as shown. Following this, all the sensor events included within the mid-height of the peaks were extracted as a single temporal cluster (Fig. 3d). The mid-height of the peaks were calculated as 50% of the height of the peak relative to whichever comes first—the last local minima before a local maxima higher than the current peak, or the global minima. This ensures that a peak which is higher than other peaks that follow it, extracts a larger temporal cluster as is the case for peak 2 in Fig. 3d. Mid-heights that contained less than two sensor events or lasted less than 60 s were discarded as noise. This 60 s threshold value for noise along with the mid-height of the peak was selected after analysing the training data with different values and peak heights until all the "Meal_Preparation" activities could be identified.

A feature of using KDE is that it can also discover temporal clusters which may represent interleaved and overlapping activities. An example of this can be seen in Fig. 3d where temporal cluster from peak 3 overlaps a larger temporal cluster from peak 2. The *stats* module from the *SciPy*[2] was used to perform KDE in Python [19].

4.2 Feature selection

The next step was to select features from the temporal clusters extracted as described in the previous section. These features are listed in Table 1.

This feature set consists of eight features, the first three being—duration (length) of the temporal cluster, the variance in each temporal cluster based on timestamps of the sensor events, and start time of the temporal cluster. The start time was corrected to the hour closest to the first timestamp of the temporal cluster. The last five features were total number of events from each sensor separately in the Kitchen. All features were normalised between 0 and 1.

4.3 Visualisation using UMAP

In order to visualise the behavioural changes by day-of-the-week, UMAP was performed to generate data points in a two-dimensional space from the eight-dimensional feature sets of the temporal clusters. It was hypothesised that using a day-of-the-week level of granularity might help to better track changes in the longer term, because as shown in Fiorini et al. [8], there can be marked differences between weekday and weekend routines.

A 12-week (3 month) period was considered which ensured that there were enough data points for identifying repeating patterns for each day of the week. Four such periods of 12 weeks were then compared to verify whether the activity patterns persist and whether any slight changes were apparent. This means analysing four sets of 12 Mondays, 12 Tuesdays, and so on. The first three of these periods were overlapping and moving forward by 1 week at a time as follows—weeks 2 to 14, 3 to 15, and 4 to 16. This was done with a view to analyse small shifts in the user's daily routine. The last period did not overlap with the first three periods and consisted of weeks 17 to 29. This was done to determine whether, if at all, user behaviour may have changed after a longer non-overlapping time period.

[2] https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.gaussian_kde.html.

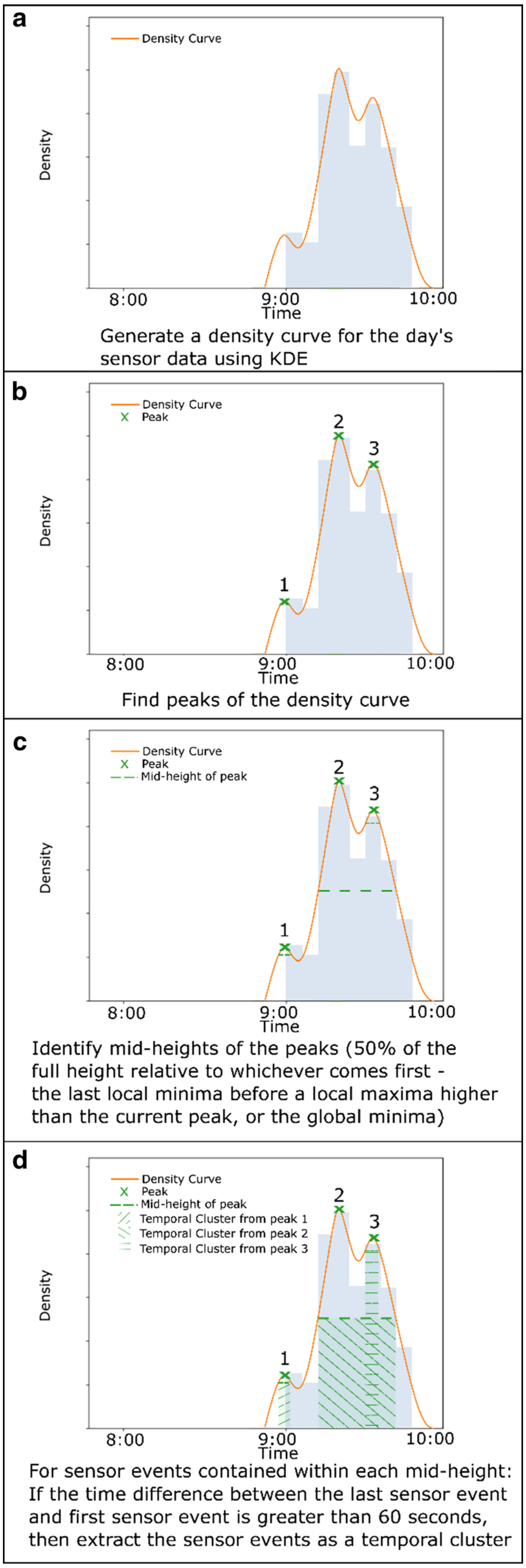

Fig. 3 Three temporal clusters extracted from the density curve generated using KDE for a single morning, overlaid with a histogram of sensor event timestamps

Table 1 Features selected from each temporal cluster

No.	Feature
1	Duration of temporal cluster
2	Variance of temporal cluster
3	Start time of temporal cluster (hour)
4	Total sensor events for kitchen sensor 1
5	Total sensor events for kitchen sensor 2
6	Total sensor events for kitchen sensor 3
7	Total sensor events for kitchen sensor 4
8	Total sensor events for kitchen sensor 5

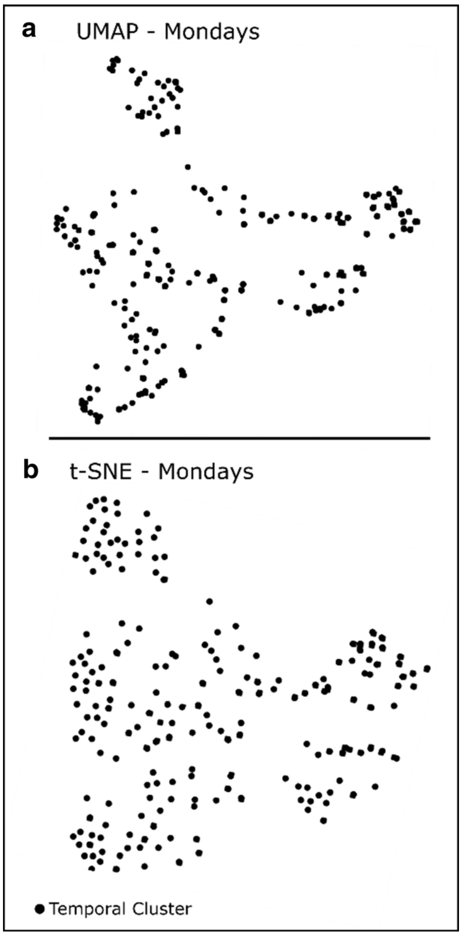

Fig. 4 **a** Top—UMAP, **b** Bottom—t-SNE (both projections are for weeks 4 to 16)

Figure 4a shows an example of Mondays for weeks 4 to 16 for UMAP. The parameter “n_neighbours” was set to 15 and “min_dist” was set to 0.1 empirically.

T-SNE (Fig. 4b) was also performed for comparison using the same data set to verify that the UMAP plot does not contain spurious artefacts. The perplexity parameter of t-SNE was determined empirically and set to 25.

It can be seen in Fig. 4 that the plots created by UMAP and t-SNE are visually similar. T-SNE plots also appeared to have a less visually discernible morphology as can be seen in Fig. 4b, which makes them harder to interpret for the sensor data. It must also be noted that t-SNE is very sensitive to the perplexity parameter and as such makes it difficult to obtain consistent and reliable results [16]. For these reasons, UMAP was favoured for visualising the patterns of activities clusters.

5 Results and discussion

This section presents the results of the KDE for extracting temporal clusters, as well as the UMAP visualisations.

5.1 KDE: extracting temporal clusters

This section presents the results of using KDE temporal cluster extraction, as performed on the Aruba test dataset for each day individually. This technique was tested on a consecutive 28-day period. Using the KDE temporal cluster extraction technique, a total of 454 temporal clusters were extracted for this period (Table 2). These temporal clusters included 100% of the labelled activities present, within an error of + or − 5 min as compared to the timestamps of the activities in the dataset. 211 additional temporal clusters (46% of the total) were also discovered, which were not associated with an activity label.

Researchers in the past have either labelled the unlabelled periods of sensor activity as an additional "Other" activity or have removed them completely [17]. In such studies, the accuracy of the activity recognition system is significantly impacted due to the presence of noise in the unlabelled sliding windows being classified. In the study presented in this paper, temporal clusters that contained unlabelled data were not removed but were included in the analysis as they could potentially represent activities that are not labelled, yet are of significance in representing the user's behaviour. Periods of low sensor activity in the Kitchen, which can be viewed as noise and not pertaining to any important activity information, were automatically removed by this technique as the density was too low to generate a temporal cluster (as explained in Sect. 4.1).

The next subsection presents the results of UMAP.

Table 2 KDE results for the test period: days 53 to 81 (total 28 days)

Labelled activities in the test period	243
Temporal clusters extracted (labelled)	243
Temporal clusters extracted (unlabelled)	211
Total temporal clusters extracted	454

5.2 UMAP visualisation

This section presents the results of UMAP visualisation. Figure 5 shows UMAP plots generated for each day of the week, for four 12-week periods (Period 1 (P1): weeks 2 to 14, Period 2 (P2): 3 to 15, Period 3 (P3): 4 to 16 and Period 4 (P4): weeks 17 to 29).

Each data point in the plot represents a temporal cluster which was extracted through KDE. As UMAP is primarily used for visualisation and clustering is generally not recommended [16], the analysis included for this approach is therefore based only on what is visually discernible.

As can be seen from Fig. 5, the UMAP plot for each day of the week has a slight triangular morphology (most evident in Tuesdays). However, each day of the week still has a distinct visual morphology that persists for at least the first three overlapping 12-week periods. Additionally, it can be observed that plots for Period 4 (weeks 17 to 29) in Fig. 5 are visually different compared to the plots for the preceding three periods, with the exception of Fridays. While we can't conclusively determine the cause of this difference, noting of the presence of similarities and differences by the carer could be used as a mechanism to prompt further investigation through a discussion with the service user. For Mondays, Fig. 6 shows the UMAP changing over time from week 2 to 29. Each plot comprises data from a 12-week period, with a step-size of 3 weeks. There is a gradual, but visually discernible shift in the UMAP pattern over time.

When comparing the number of temporal clusters between the individual days of the weeks over all the four time periods, it can be seen in Fig. 7 that the number of temporal clusters is lower on Wednesdays and Thursdays. As the number of temporal clusters is indicative of the overall level of activity, this information could provide useful insight for the carer as to user's different activity levels over the weeks.

Furthermore, in Fig. 7 a trend of a reduced number of temporal clusters for Period 4 can be noted when compared to the previous periods 1, 2 and 3. This is particularly evident for Tuesdays and Fridays.

5.2.1 Radar graph comparison

In Fig. 5, it can be seen that in addition to the overall UMAP cluster morphology, the level of dispersion of the points is also different for different days of the week. For example, when comparing Mondays to Thursdays in Fig. 5, a difference in the dispersion of points between Mondays and Thursday is visually discernible, i.e., the UMAP for Mondays has areas of varying density of points, while the UMAP for Thursdays is comprised of more

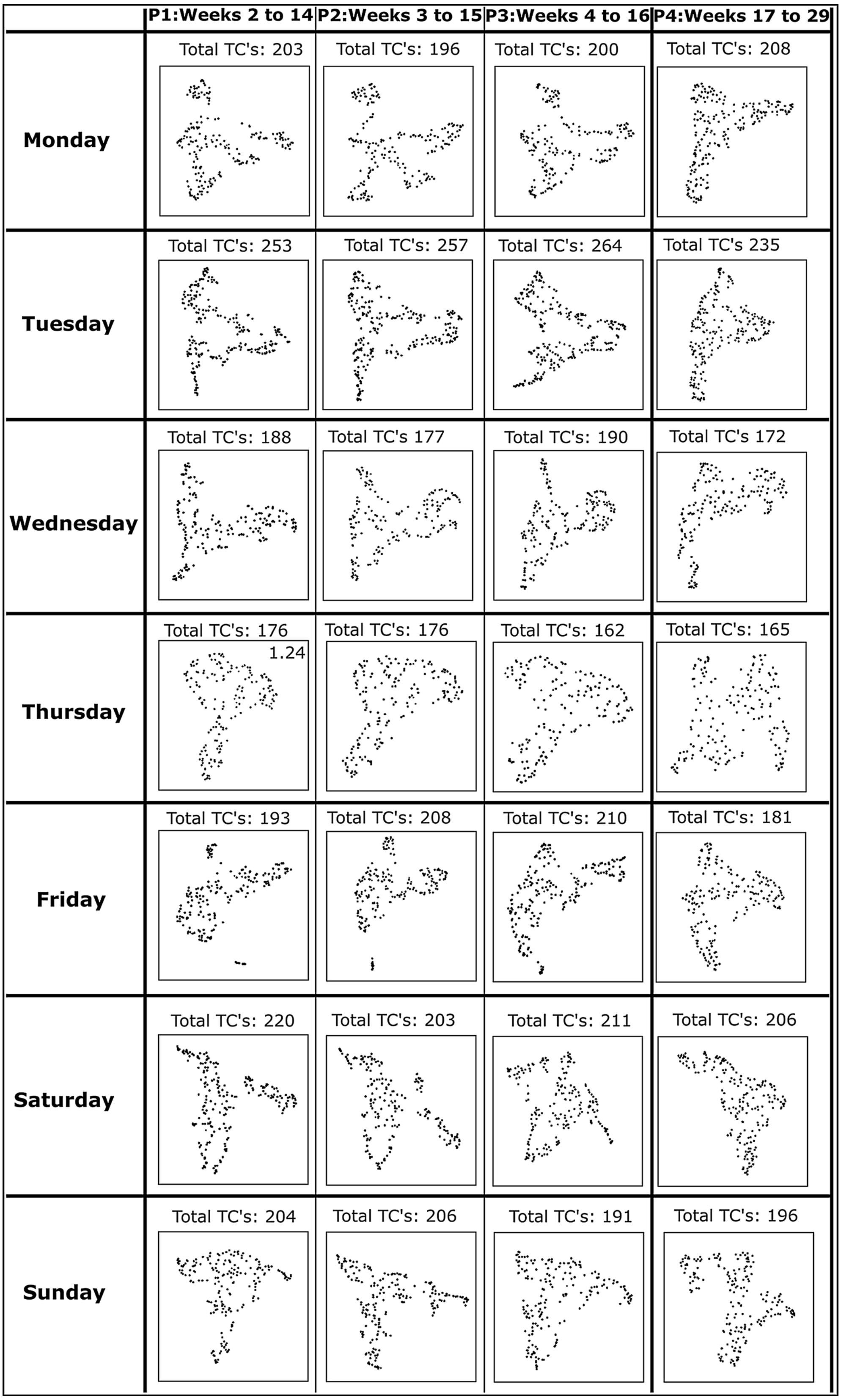

Fig. 5 UMAP visualisations for each weekday for three overlapping 12-week periods, and one separate 12-week period. Total TC's—total number of temporal clusters

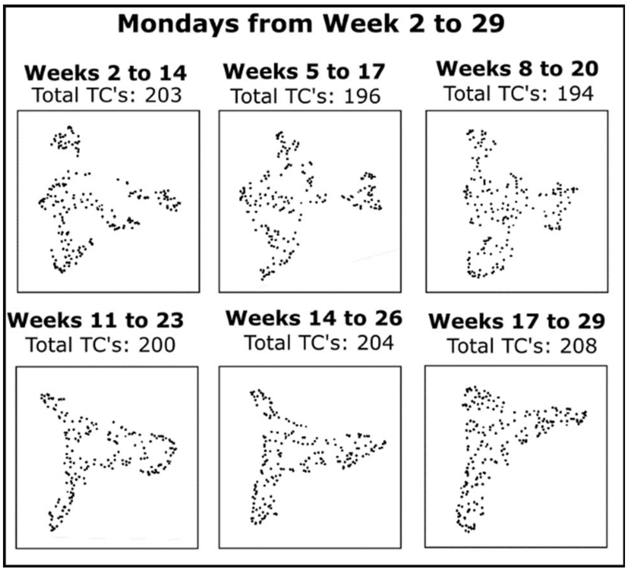

Fig. 6 UMAP for Mondays for 12 week periods moving forward by 3 weeks at a time, from week 2 to 29

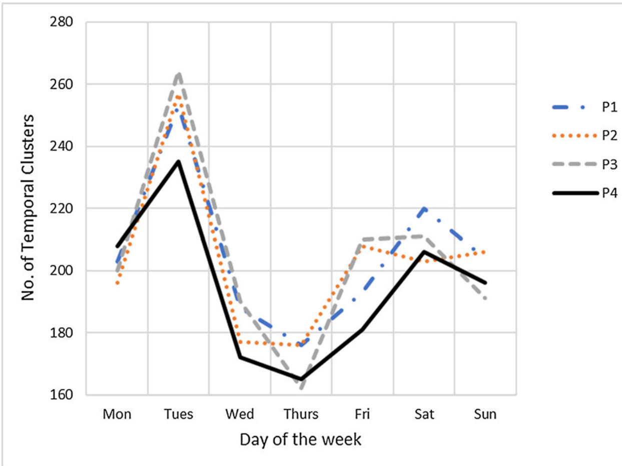

Fig. 7 Graph comparing the number of temporal clusters between the four time periods (P1, P2, P3 and P4)

uniformly distributed points. This could be partially explained by the lower number of temporal clusters present on Thursdays as shown in Fig. 7; however, Thursday for P4 has more temporal clusters than P3, but the data points in the former are still more dispersed, with a less distinct morphology. To gain further insight into these differences, radar graphs were generated for Mondays and Thursdays to identify the total number of temporal clusters at different times of day (ToD), similar to the approach presented by Fiorini et al. [8].

The radar graphs presented in Figs. 8 and 9 also show the standard deviation for each ToD over the 12-weeks. The activity, as represented by the number of temporal clusters at different times of day, in the radar graphs for P1, P2, and P3 are more similar to each other, while the radar graph for P4 shows different activity levels at different times of day for both Mondays and Thursdays. This correlates with the differences in the dispersion pattern of points in the UMAPs from Fig. 5.

When comparing Mondays to Thursdays in Figs. 8 and 9, Mondays indicate a more regular routine than Thursdays. This is also corroborated from the lower standard deviation for the majority of the ToD clusters for Mondays when compared to Thursdays. This relates to why the UMAP for Thursdays is more spread out and less distinct when compared to Mondays.

For both Mondays and Thursdays, the standard deviation for P4 is the highest (reaching a maximum of 2.21 and 2.13, respectively). The radar graphs show a more varying pattern of activity for different times of the day during P4 than during the previous periods P1, P2 and P3. The UMAPs for Thursday also indicate differences between the first three periods and P4. It should also be noted that as can be seen on the P4 radar graph for Thursdays, there are two ToD's with a standard deviation higher than 2, which could explain why the UMAP for Thursdays in P4 is much less distinct in terms of morphology and distribution.

This analysis goes some way in explaining how the UMAPs in Fig. 5 encapsulate information about the regularity of a user's routine, as when the user has a more fixed and repeatable routine, the corresponding UMAPs show a more distinct morphology and dense dispersion pattern of points. It must, however, be noted that the UMAP encodes more information from the temporal clusters than the one parameter shown in the radar graphs, as the UMAPs are generated using the full feature set as presented in Sect. 4.2. Therefore, while the radar graphs show the total number of temporal clusters for each ToD, the morphology and dispersion density of points in the UMAP plots encapsulate much more information than just the temporal clusters. Visualising the activity data through UMAP is put forward as a visualisation technique which could enable carers to identify changes over time. It is envisaged that if a visually discernible change was noted, the next step would be for the carer to examine the specific activity data in more depth and initiate informed discussions with the service user to understand what may be causing these changes and suggest appropriate interventions if the change is detrimental to their well-being. For further objective analysis of the data, pattern recognition and blob analysis to automatically detect changes in the user's routine based on the changes in the morphology and density patterns of the UMAP plots could be carried out. This would allow the system to then automatically flag changes in the user's routines as well as notify the user and their carer.

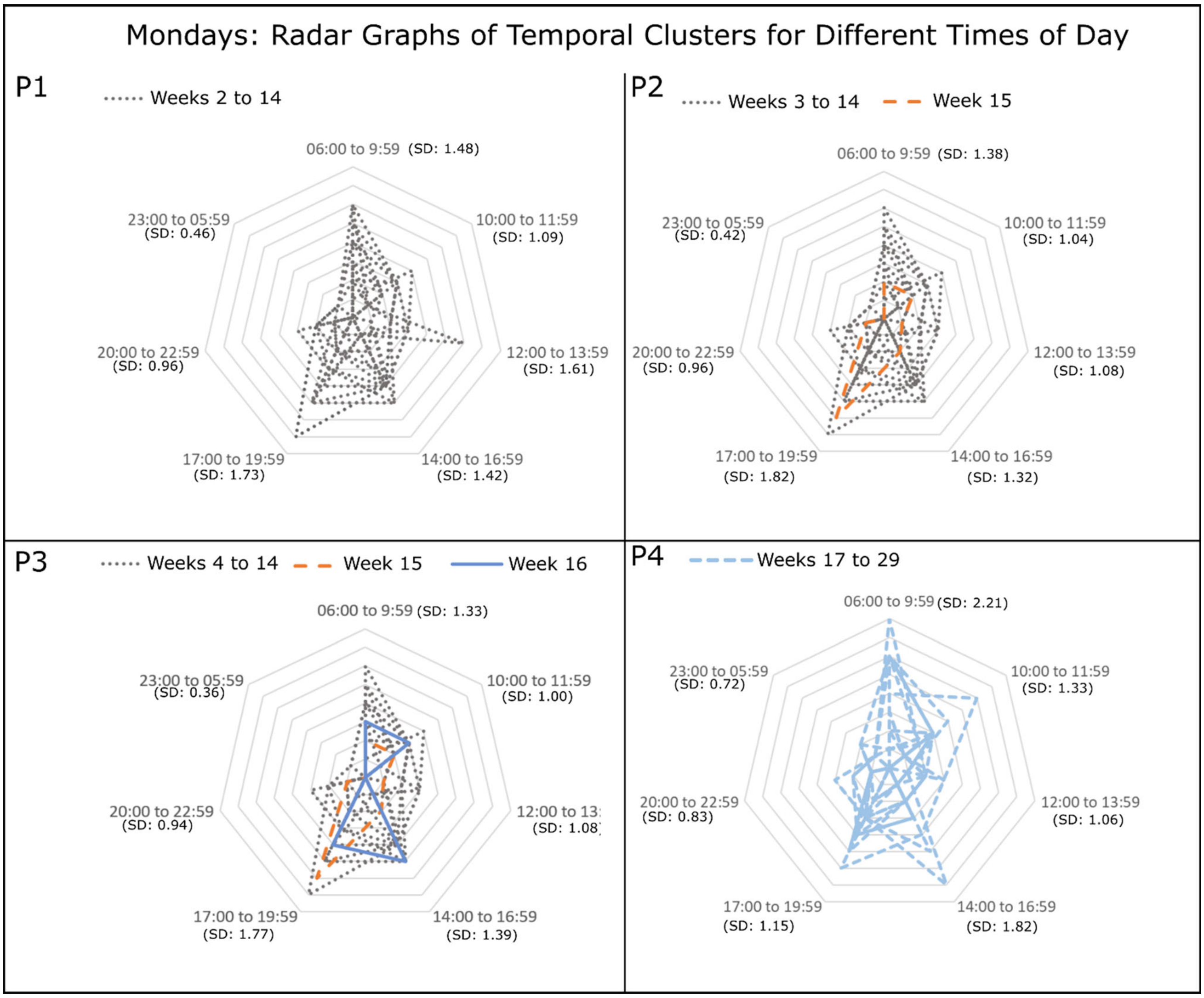

Fig. 8 Mondays: Radar graph for each 12 week period showing the total number of temporal clusters at different times of day. SD = standard deviation in total number of temporal clusters for that time of day. P1, P2, P3 and P4 refer to the four time periods included in the analysis

6 Conclusions and future work

This paper illustrates how unsupervised learning techniques can be used to discover activity patterns in unlabelled data from WSNs such as PIR sensors. A key advantage of this methodology is that it does not require hand tuning of parameters for the unsupervised learning methods. KDE is used for automatically extracting periods of dense sensor activity, as opposed to using of traditional fixed length sliding time and sensor windows. The benefit of using KDE is that the parameters can be statistically derived from the data and the method is not reliant on a fixed time window set by the user.

As carers are already overworked and have limited time for each user, it is crucial that the time they spend with the service user is utilised efficiently. The work presented in this paper revealed through UMAP and KDE, that individual week-day data, considered over long periods, could contain unique features that can be used to infer user activity levels and track any changes over the long term. The information discovered through UMAP visualisations could be further utilised as part of a structured process or assessment protocol which helps to identify anomalies or changes in user activity. This could then be used for supporting carer–patient interactions, or even tracking the effectiveness of interventions and medication on the user's health condition as indicated by their activity or changes to routines over time.

As one of the noted limitation of this study is that it is based on a single user's data, it would be important to test the methodology presented on a larger number of users, acknowledging that the method of relying on motion

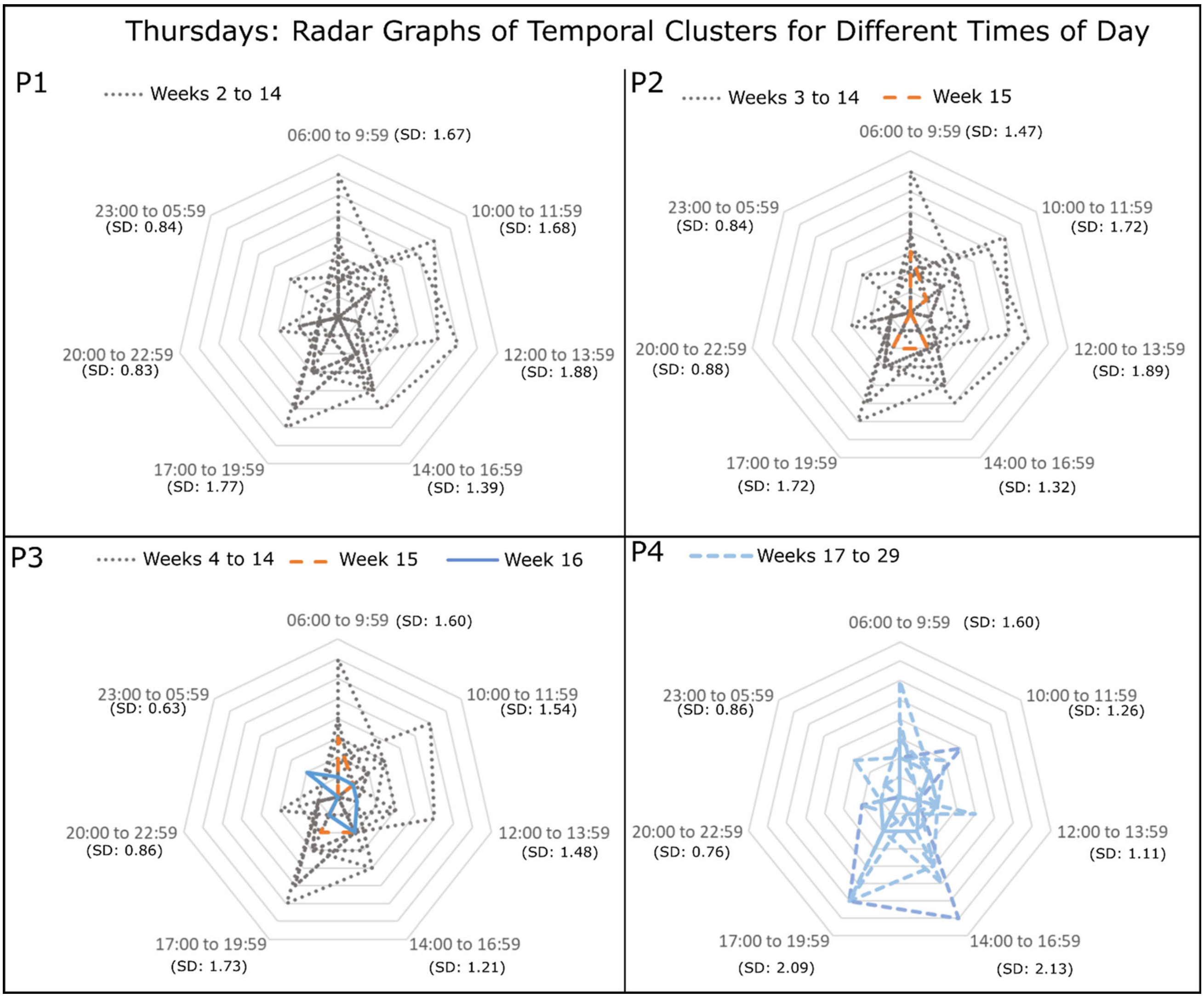

Fig. 9 Thursdays: Radar graph for each 12 week period showing the total number of temporal clusters at different times of day. SD = standard deviation in total number of temporal clusters for that time of day. P1, P2, P3 and P4 refer to the four time periods included in the analysis

sensors might not be able to track an individual's activity in a multiple occupancy scenarios, unless additional sensing is used to track an individual occupant as well.

This paper presented a novel approach to generate actionable information and insights on changing user activity over time from unlabelled data in an unsupervised manner. Future work will involve developing a real-time implementation using the KDE temporal cluster extraction technique, as well as testing on other datasets, and trialling UMAP and radar graph visualisations based in the real-world with carers and their service users. The use of pattern recognition and blob analysis will also be investigated to automatically detect and flag changes in the UMAP plots over time in order to generate notifications to the user as well as their carers. The underlying aim of this work is to develop a system that can support the user, as well as their carers, by providing actionable information based on learning their activities and routines and tracking any changes to these, without the need for labelling large amounts of data or the use of intrusive devices such as microphones and cameras.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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Intelligent IoT System Requirements to Support Self-Management for People with Learning Disabilities – A Study with Care Providers

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***Abstract*— Internet of Things (IoT) technology and Smart Home (SH) solutions are a growing area of research and development, particularly within health and social care where they have potential to offer information and support for self-management and independent living. However, successful design and deployment of these technologies are predicated on a clear understanding of user aspirations, needs, and requirements. This paper presents findings from seven one-to-one interviews with care staff who contributed their experiences representing a diverse range of job roles and categories of service-users supported. Our participants were from a regional supported-living provider with facilities for people with learning disabilities. The interviews provided insight into care service provision and service-users' needs, as well as helping to identify areas of the current service that can be supported by IoT based intelligent systems. The feedback that staff provided was based on their knowledge and understanding of the needs of specific service user groups and included information regarding the appropriateness and applicability of the technologies, as well as the appeal, acceptability and usability of these solutions.**

Keywords*— *internet of things, smart home sensors, learning disabilities, data visualisation, design requirements.

I. Introduction

According to the UK department of health [1], the term learning disability (LD) is defined as a "significant reduced ability to understand new or complex information, to learn new skills (impaired intelligence), with a reduced ability to cope independently (impaired social functioning), which started before adulthood." Approximately 1.5 million people in the UK have LD, and 1.2 million of the people with LD are in England based on prevalence rates from Public Health England [2] and population data from the Office for National Statistics [3]. 905k of these people were adults aged 18+ (530k men and 375k women) [4]. This constitutes around 2.16% of the adult population. Historically, people with LD were placed in "institutions" but in late 1980s a wave of change saw the closure of these institutions and resettlement of people with LD in the local communities in smaller residential homes. This includes the drive towards people with LD being supported in their own homes where care is tailored to the individual needs and independence is promoted. Currently, the move to independent living is also partly driven by a policy of austerity where social care is struggling with funding and staffing issues [5].

The Internet of Things (IoT), in the context of Assisted Living, can be summarised as the embedding of everyday objects with networked sensors, actuators, and relays, which are connected to local or cloud-based data servers. Intelligent systems that utilize these IoT devices are then used to perform various forms of automation as well as data analytics [6]–[8]. An ecosystem of IoT devices and intelligent systems comprises a Smart Home (SH). Over the past decade, there have been major advances in such SH technology which demonstrate a significant potential to enable people with physical and cognitive impairments to live independently in their own homes [9]. The goal of such SH technology is to combine user activity data with relevant a priori information and provide actionable insights which can be used, for example by care staff to tailor their support as appropriate. Additionally, this information can also be used to provide context aware assistance to the user for self-management. The use of scripted task prompting to support self-management has previously been explored [10]–[12]. However, real-time analysis of sensor data in relation to previous patterns of activity can ensure that the prompts are not just simple scripts previously set-up, but in fact are personalized and relevant in the given situation.

Key challenges for successful adoption of any assistive technology from the end-user's perspective include a) acceptability and b) relevance and c) usability. These can be addressed by taking a co-design approach, which lies at the heart of a social model of disability and support [13], [14]. This involves ensuring the participation and inclusion of the service user in shaping how the technology can be best integrated into their lives. Wilson et al., 2015 noted that a clear understanding of the service-users of such technology and a user-centric vision was missing from the research field. Wilson et al. also emphasised the importance of working with carers so that simple and low-tech solutions to improve the usability of such technology can be identified. In fact, their input can also be important to understand how best such technology can be integrated into existing housing so that it blends-in to the surroundings in order to appeal to users and keep them 'in control' [16].

Additionally, new challenges of eliciting requirements including communication issues from this particular user group of people with LD must be taken into account. These challenges are attributed to the limited ability of people with LD to provide input depending on their condition, difficulties in gaining consent, and the inability to get adequate representation due to very diverse needs [17]. Hence, working with domain experts such as the care providers can serve as an ideal starting point for establishing support requirements as well as identifying crucial barriers and opportunities in the initial stages of the design process. Thorpe et al., (2016) [17], claim that the care provider's perspective on user-requirements can offer insights into diverse and varied experiences, trends, scales and proportions regarding the service users' needs and support requirements.

Accordingly, our key objectives in this study were to:

1. Identify gaps in the current care provision for people with LD and acquired brain injuries in performing Activities of Daily Living (ADLs)
2. Gain an understanding into the appeal, acceptability, and appropriateness of off-the-shelf SH sensors from the perspective of care staff
3. Identify how SH devices could be incorporated into interventions that could augment the support provided by the care staff
4. Receive feedback on different types of activity-data visualisation techniques, in relation to the type and level of information required by care staff and how they might use this information
5. Explore emerging design requirements for future development of assistive SH solutions including ethical considerations relating to privacy and security.

These objectives were used as the basis of the interview plan, however the subsequent analysis of the interviews were performed using an inductive approach. The next section of the paper presents a review of related literature, followed by the details of the methodology; Section 4 presents the findings of the interviews, before delving into the discussion about SH development in section 5, and finally section 6 provides the conclusions.

II. Literature Review

LD significantly reduces an individual's ability to understand new information, learn new skills, and cope independently [1]. Therefore, people with LD often require assistance and supervision in performing ADLs. The majority of the existing literature that investigates technology to support people with LD is focussed on education and making learning more accessible [18]–[21]. Authors in [22] provide insights into the effectiveness of technology in supporting people with LD, focussing on adolescents and young adults with LD in secondary and post-secondary education settings. Their research highlights communication issues being a barrier for people with LD, which would need to be considered when investigating support requirements for people with LD.

An area of research within IoT and assisted living is the use of sensor data to recognise activities and evaluate changes in the health of the user through tracking changes in their activity patterns over time. Authors in [23] investigated the minimal number of sensors required in order to provide wellness evaluation for the users. To do this, they utilized the concept of "busyness", defined as the aggregation of movement and activity within a home [24]. This "busyness" metric was then visualised in the form of a radar graph that shows how active a person has been throughout the house at different times of the day. Another study used long-term data from a public SH dataset to find patterns in a person's activities over multiple weeks [25], therefore, as part of our research we are also interested in investigating the utility of providing these forms of sensor data analysis to carers of people with LD. This is done to gain feedback from them on whether tracking activities through sensors would affect the service users' ability to self-manage, and also gain insights into the impact of any interventions.

A number of user-engagement studies involve conducting interviews, which require qualitative analysis. Systematic qualitative analysis can be challenging, however authors in [26] highlight the benefits of using 'The Framework Method', particularly when analysing interviews, as it provides a structured approach for objective analysis, particularly for researchers more conversant with quantitative analysis. An important point highlighted by the authors, which was originally iterated by [27], underlines the importance of sampling qualitative research for capturing diversity around a phenomenon, rather than purporting to represent a wider population. The authors add that the aim of a qualitative healthcare study should include shedding explanatory and predictive light on important phenomena while contributing to the improvement of health services and development of health policy. The guidelines and suggestions provided by the authors have informed the analysis conducted in our paper.

III. Methodology

The participants in this study were care professionals recruited from a regional supported living provider with facilities for supporting people with LD. We focussed on ensuring cohort diversity in terms of job roles, level of experience, and categories of service users supported. A total of seven care staff were interviewed. Their service users ranged from young adults with acquired brain injuries to older adults with learning disabilities. The interview consisted of a number of topics relating to their interaction with the care service users when supporting with ADLs. This was done with a view to gain insights into the care service and service users, as well as identify areas of the current service that can be supported by assistive technology. During the interview, the care staff were also shown examples of SH technology and also of how sensor data might be presented or visualised to support their understanding of their service users' needs. Feedback was sought on the appeal, acceptability, and usability of these solutions from their perspective, as well as their knowledge and understanding of the needs of specific service user groups in relation to the appropriateness and applicability of the technologies. All the topics discussed during the interview were selected based on the objectives of the study as listed in the Introduction.

The first part of the interview served as an introduction to the research context and the structure of the interview. The second part of the interview focused on the staff members and their experience with service users. This was in the form of an open-ended discussion about their overall experience with the service users. The participants were requested to keep their service users' identities anonymous at all times. The third part of the interview served as a demonstration and discussion of SH technology during which commercially available devices listed in TABLE *I* were physically handed to the participants to evaluate. These devices have been selected based on commercial availability as well as usage in existing literature by other researchers focussing on SH and assisted living [28]. The final part of the interview comprised of showing staff members four different data visualization approaches as examples of varying ways in which sensor data could be presented to display snapshots of information on a person's day-to-day activities over different periods of time.

TABLE I SH devices shown during the interview

SH Device	Functionality
Contact Sensor	Opening and closing of doors, windows and drawers.
Multi-Sensor	Movement of the person in the room, light levels, and temperature
Smart Plug	Switching on and off of appliances (kettle, microwave, iron, etc.)
Smart Thermostat	Monitor temperature of the house
Smoke Sensor	Detect cooking in the kitchen
Flood Sensor	Usage of sink in the kitchen

All the interviews were audio recorded, transcribed verbatim, and analysed using an inductive qualitative approach. The inductive analysis revealed eight key themes presented here in descending order of number of coding references: service users, visualisations, use-cases, support background, technology, acceptability and privacy related issues, prompting, and rehabilitation. These key themes and their associated sub-themes contributed to the construction of profiles for staff and service users, identification of types of activities that can be supported by IoT based intelligent systems, as well as determining specific requirements for personalising prompts and visualisation of sensor data. The coding was conducted using the qualitative data analysis tool Nvivo [NVivo qualitative data analysis software; QSR International Pty Ltd. Version 12, 2018].

IV. Staff and Service user profiles in the context of the care facility

The care staff interviewed included three project managers, two project co-ordinators, and two support workers. In the context of this care facility, a "project" comprises a cohort of service users with specific LDs living in a particular type of facility. The support workers work directly with service-users for supporting them with ADLs. The project coordinators are in charge of analysing support requirements of service users and assigning support workers accordingly. While project managers are in charge of managing project coordinators. All the project coordinators and managers interviewed also had previous experience of working directly with service users prior to their current position.

The amount of experience the staff had ranged from 5 months for a support worker to 25 years for a project manager. Two out of the three project managers were aware of SH devices although they did not own any such devices themselves. One of the project managers was not familiar with such technology and admitted that they were sceptical regarding the feasibility of such solutions. Both the project co-ordinators were familiar with SH technology and one of them also owned a smart meter and smart thermostat. One of the support workers had used SH technology while the other support worker was aware of them but had never used them. The latter also described themselves as a 'technophobe'.

The following sections present the findings of the interviews as discussed in relation to the care staffs' service users.

A. Challenges in Daily Living

Various challenges in daily living for the service users were identified through the interviews. These included common issues which cause the service users distress and make their activities even more challenging.

1) Patterns and Routines: Three of the staff members expressed that young adults with LD require patterns and routines in order to complete tasks, and dislike any new changes. It was also pointed out that when a particular member of staff was on leave, they get temporarily replaced with a new staff member which can upset the service users.

2) Building Independence: The project managers revealed that the service users like to feel independent, and therefore the service users feel frustrated whenever their indpenedence is taken away. One way to build this independence is to introduce gaps in the care service provision during which the service users are left to function independently for a set period of time. It was also highlighted that the care staff have to be careful as to not make the service users more dependent on them than required, therefore they instruct the service users to perform tasks themselves whenever possible.

3) Communication Issues: Two of the staff members have service users with specific communication issues. These service users become increasingly frustrated and anxious when they are unable to communicate with their carer. It was also mentioned that communication issues can combine with other problems, a specific example was given regarding a service user becoming incontinent at night but being unable to communicate this issue with the staff.

B. Impact of Social Co-Habitation

As most of the service users live in shared facilities, they have to share common areas when performing everyday activities. Two staff members stated that their service users have known each other for a long time and have developed a friendship. They often perform certain activities together adding a social element to them. On the other hand, another staff member described their service users as "incompatible most of the time", and would generally stay in separate areas of the house during the day. They did, however, have friends from outside the house that would visit them. This sentiment was reiterated by another staff member who provided a similar answer describing their service users as "separate individuals who like very different things".

C. Areas of Support

All the service users discussed by the care staff during the interview require either one-to-one support or monitoring, of all kitchen-based activities. In addition, some of the service users also need assistance and prompting with morning activities, personal hygiene, washing clothes, and medication management.

1) Kitchen Activities: The amount of support required for kitchen activities varied from person to person. Some service users were able to prepare snacks which require the use of a kettle or toaster by themselves, but needed supervision for cooking meals. While other service users were able to operate the hob unsupervised but still preferred to wait for the staff for prompts.

2) Morning Activities: Four staff members mentioned their service users struggled with getting up in the morning and require a lot of prompting to take action for tasks such as brushing their teeth and showering. The prompting required ranged from verbal prompts to visual aids.

3) Night-time Activities: Four staff members highlighted the need for night-time monitoring. This included sleep monitoring as well as monitoring activities in the kitchen. The latter is specifically due to some service users who were instructed to not snack at night as it caused issues with their sleeping cycle.

4) Medicine Management: Three of the staff members were confident that their service users could manage medication independently if they had "the right technology to remind them". However, one staff member mentioned an instance where their service user who had an automated pill dispenser still required supervision to make sure that the medicine was taken. Another staff member gave an example where a particular service user forgot to take morning medications, which was discovered when the care staff perfomed their routine visual check of the medication drawer at the end of the week.

5) Life Skills: Some staff members also stated the importance of supporting the service users with life skills to help them become more independent over time. This included helping them learn how to cook, manage their home, manage their time, and "understand the world around them including building relationships". A suggestion was made by one of the staff members that the support should be tailored to focus more towards teaching life skills rather than just helping the service users in completing tasks.

D. Familiarity with Technology

It is important to establish the familiarity and relationships of the service users with different types of technology, as this would indicate the feasibility and usefulness of off-the-shelf SH products and influence development of future technology.

1) Kitchen and Household Appliances: One staff member had a service user who was very capable of finding and using helping aids by themselves. This included purchasing a slow cooker which they now use for cooking. Another staff member had service users who could operate the dishwasher by themselves. In contast, two of the staff members said that their service users were not very proficient with such technology, and struggled to use appliances like the washing machine. One of these staff members attributed this to the service user's memory issues rather than their capacity to understand how the appliance works.

2) Smartphone Apps: One staff member mentioned that their service user is currently trialling an app called "Brain in Hand", which is suppoed to help the service user become more independent by monitoring their anxiety and building strategies to cope accordingly. Another staff member has a service user who is able to use their smartphone confidently and often sets reminders themselves to help throughout the day.

3) Smart Home Devices and Sensors: The staff members had various service users who had experience with SH technology. This included service users who had used smart plugs to control their lamps from their smartphone, smart blinds and windows, and a smart speaker. One service user had turnstiles with sensors at the entrance of their flat which helped monitor when the service user would enter/exit their flat. One staff member had service users with sensors installed for sleep monitroing, and went on to describe them as "young and techy". Another staff member recounted a particular incident where their service user had motion sensors installed by the council for monitoring night-time activity after the service user was found to be constantly tired during the day. The sensors were installed with the service users's permission, however the service user later removed the sensors from the walls.

4) Other Technical Proficiency: One staff member has a service user who is skilled in woodwork and electrical work, and is generally open to new technology. Another staff member has a service user with communication issues who is able to use a speak box and is very proficient at typing.

V. Feedback and Use Cases

This section refers to the part of the interview where the carers were shown SH devices as listed in Table 1 as well as visualisations, and were asked about how their service users would perceive these devices. These visualisations included a bar chart showing different durations of kitchen activity, a radar graph showing different levels of activity around the house, and a visualised floor plan with varying shades of colour overlayed on each section of the house to represent the amount of activity occurring in that section. These visualisations were chosen to represent a range of different visual styles as well as granularity of information.

The following subsections present the findings according to the care staff roles.

A. Feedback to Smart Home Devices and Sensors

1) Project Managers: The answers provided by the staff members varied according to their experience with different user groups. One project manager said that in general their service users would be quite clear about understanding the sensors and devices that were shown during the interview, and would therefore be able to consent whether they want them or not. They predicted that their service users would be happy to use the devices but some of the younger service users may be playful and could interfere with them once installed. Another project manager provided a similar answer saying some of the service users would have the capacity to understand the sensors and devices and provide consent. The third project manager said that most of their service users are not proficient with technology as they are mostly older people with LD. They also mentioned that these service users have experienced the older institutionalised facilities and therefore were sceptical regarding the use of any sensors for monitoring.

2) Project Coordinators: One project coordinator was concerned that all of their service users would not understand the purpose behind the sensors and therefore could not provide consent. There was also a concern that the service users might find them too intrusive. In contrast, the other project coordinator interviewed predicted that most of their service users would be happy to have SH sensors and devices installed in their flats.

3) Support Workers: One support worker said that even though their service users sometimes struggle with appliances due to memory issues, they still have the capacity to understand what the appliances are for, therefore they felt confident that the service users would be able to provide consent. The other support worker interviewed predicted that their service users would be able to grasp the purpose behind the sensors and device, and would accept their use. An important point made by this support worker was that the service users had already consented for the care staff to maintain food and mood diaries in order to track their behaviour. Therefore, they suggested that the use of sensors to track their service users' activities would not be a very different concept for them.

B. Feedback on Smart Home Sensor Data Visualisations

1) Project Managers: It was suggested that the visualisations could be used to monitor how active the service users were during the gaps in their service provision. The project manager added that this could be used to alleviate concerns that care providers have for service users receiving minimal support regarding whether they are performing activities on their own or just waiting for the carer to come and engage. The staff member went on to talk about a service user who quickly jumps to the conclusion that they have failed when stuggling to perform a task. And that verbally telling the service user that they have improved at the task is not enough to convice them. It was suggested by the project manager that having access to visualisations which can track changes over time could prove beneficial to objective show the service user that they are improving and boost confidence. It was also highlighted that the project manager is worried that their service users "may be moving backwards rather than forwards" regarding independence. And that visualisations could be used to support service users in becoming more independent. Another suggestion made by one of the project managers was that visualisations could be used to measure the social interaction of the staff members with service users. This could in-turn be used to evaluate which staff members have a more positive impact on a particular user and further tailor the service provision accoridngly.

2) Project Coordinators: One project coordinator suggested that the visualisations would be more appropriate for service users that are more independent. They suggested that visualisations could be used by service users with memory issues to track how active they have been throughout the day and whether they have been using the bathroom regularly. It was suggested that the focus of the visualisations should be less on monitoring and more on self-management. Another project coordinator mentioned that monitoring and visualisations focussed towards medicine management would be more helpful for their service users. It was also highlighted that there must be a way of customising the visualisations for each individual user, so that they select the level of information displayed. Additionally, they suggested the use of visualisations in order to evaluate the support needs of new service users. However, they raised caution with regards to visualisations increasing the anxiety of certain service users.

3) Support Workers: It was pointed out by a support worker that the visualisations could be especially useful for kitchen activities. As their service users need to follow a diet due to health concerns but they often end up preparing snacks in the kitchen. Another support worker mentioned that as their service users live together in a shared facility, instead of focusing on tracking individual users it may be benficial to track overall activity in the house. This would be used to see which rooms of the house are most active at certain times of day, and therefore support could be tailored for everyone accordingly. It was however mentioned that the service users have separate cupboards and drawers in the kitchen, which could be utilized to identify which user is in the kitchen for tracking kitchen activities. Another important point was that service users may change their mind from day to day regarding the monitoring and visualisations, therefore there needs to be a way for them to control the data they want to share with their carer.

C. Support Opportunities

Further to the visualisations, certain new use-cases of technology based on the SH devices were also suggested by the care staff. A suggestion was made that if the sensors can be used to detect when someone suffering from obsessive compulsive disorder was having an episode, the SH could automatically play soothing music. One staff member was also concerned about the heating, as their service users often set the heating too high "to the point where it can start affecting their health". It was recommended by another staff member to use smart thermostats to address this issue. A suggestion was also made to use voice activated control for certain appliances, along with automated prompts for making sure the house is secure at night (doors locked, windows closed, etc.). Automated prompts were something every staff member suggested would be helpful for their service users. However, most of them pointed out that it was important that the prompts are not too repetitive so as to annoy the service user or induce further anxiety.

VI. Emerging Design Requirements

Based on the findings presented in the previous sections, this section will further discuss the emerging design requirements for assistive SH solutions along with barriers which must be addressed. While a number of possible use opportunities for supporting people with LD have emerged, the issues highlighted by the care staff have generated a number of specific non-functional requirements which need to be carefully considered. A number of these are specific to people with LD and take into consideration the need to improve their capacity for self-management and assert their independence.

A. *Achieving Balance between Independence and Level of Support*

As mentioned previously, assessing an individual service users' support and care needs is an area which can be supported by the technology. IoT sensors could be embedded in the user's environment to establish a baseline of their activities, as done in [23], which can then be supplemented by additional information from the user through carer-user interaction. This process could help care staff in assessing the service user's support needs on a more continuous basis and tailoring and adapting their support plan accordingly. This is fundamental to preventing stymying of new skills development, while ensuring that the correct support infrastructure is in place to promote safety and facilitate a good quality of life. As such, integrated sensors would continue to monitor the user's activity and generate visualisations so that changes in the user's health can be inferred and their support plan can be adjusted accordingly by staff. In addition there is also an requirement to present the information in a way that empowers the service-user to recognise their own progress and seek encouragement from their achievements. Therefore, enabling self-evaluation would not only be beneficial for the service-users, but could become a means by which improved planning and resource allocation from a care perspective could be achieved. Using SH user-interaction to elicit the service-user's confidence, self-awareness, and perceptions of the quality and completion of a task, presented in conjunction with quantitative data from the sensors, could provide the ability for the service user themselves to flag when and what support they require. Longitudinal monitoring could help to track performance against a range of personalised metrics.

B. *Monitoring and Supporting Gaps in the Care Service Provision*

From the previous section it is noted that "lack of independence" is a major source of frustration for the service users and that independence is promoted by introducing small gaps in the care service provision of the user. Introducing gaps in the service allows the user to act by themselves and be responsible for themselves. However, these gaps also increase the risk of the user not being able to manage on their own, this is exacerbated for user's who have communication issues. Therefore, through sensor data analytics, visualizations can be created for the care staff to review and evaluate how well the individual is coping by themselves. The ability to function independently can be further supported through the use of intelligent systems to provide assistive interventions during the gap in the care service and then monitoring and measuring responses to discrete instructional steps to gauge impact. This approach means that a well-developed process of promoting independence can be used more confidently by carers, who can be assured of a scaffolding of interactive support provided through a collaborative SH environment.

C. *Enabling Self-Management of Activities*

It is crucial that the service-user does not become less independent, or conversely, more dependent on the technology or on the carers. Therefore, the concepts of co-learning and reablement as described in [29] are critical for the development of technology to support independence. This could be achieved by providing feedback on evidence of achievements in an easy to understand and actionable manner, and also augmenting this with the functionality to enable the service user to query the SH for further and fuller instructions, repetitions or clarifications, or by using a coaching approach. A coaching approach, particular to support self-management, involves facilitating the service user to find solutions or plan next steps themselves through adopting a reflection questioning strategy. Furthermore, using historical data as evidence of previous behaviour, for example, could be used to motivate behaviour change. Another aspect to addressing the requirement to enable self-management is to ensure that the instructions and steps are personalised based on initially, the carers' knowledge of the user, and then later the ability for the service user themselves to adapt the system or interact with it in a flexible manner. This means that the focus of the analysis shifts to collaboration to promote the service users' active involvement in their own care.

D. *Dealing with Multiple Occupancy Situations*

Unlike a number of emerging SH and IoT solutions that are focussed on providing support for independent living for older adults where there tends to be an assumption of single occupancy, the living contexts where people with LD might reside often include shared accommodation, where there are communal living and cooking areas, and shared bathroom facilities. As such, the need for the SH system to be able to distinguish between users can be achieved through the use of interactive SH solutions using machine vision for person recognition, together with individual person tracking through integrated sensor systems. An example of the latter is the use of sensors embedded in kitchen drawers, as the care staff have confirmed that different service users have different drawers/cupboards, these sensors could be used to identify the service user(s) present in the kitchen.

E. *Requirements to Address the Barriers to Smart Home Technology*

1) Maintaing Routines and Familiarity: Ensuring that SH sensors are integrated into the built environment or embedded into familiar objects can help with preventing upset and anxiety by making them less conspicuous. At the same time, from an ethical perspective it is important that the system is transparent to the user, in terms of what data is being collected about them, and who has access to this data. It is also important that intervention techniques (such as automated prompting) are developed in a way so as to not upset the service user's routine, but rather support the service user in completing activities as part of their own initiative and agency, maintaining their routines as much as possible.

2) Privacy and Acceptabilitey: Service users need to trust the technology will preserve and respect their privacy. However, if personal activity data is to be shared with their carers to support them, then this can represent a difficult situation where the person with LD could be left feeling vulnerable or disempowered due to others having access to their personal routines and habits. Particularly if this information is then used in what might seem to them as coercive and affecting their agency. It is therefore important to personalise the way the activity data is shared for each service user according to their preferences. This personalisation also needs to be flexible and simple to perform as the service users may change their mind from day to day depending on their mood or other factors.

3) Carer Skills Development and Ensuring Confidence in the use of the Technology: Another topic which emerges is around the skills that are needed by carers to integrate this technology into how they support their service user [30]. Adopting a user-centred design approach can help to ensure that the technology developed is amenable to existing processes and skills, or identify what and where additional training is needed. However, this could also mean that the solutions might get locked into sub-optimal operational processes which originally might have been developed to deal with more systemic and organisational issues. As such, understanding technology skills needed to maximise utilisation and adoption, as well as noting current inefficiencies in the systemic procedures, can be an important part of ensuring sustainability and viability of these emerging technology solutions.

VII. Conclusion

Before designing and developing any assistive SH solutions, particularly those which support a user group with very specific conditions and sensitivities, it is important to gain a clear understanding of the particular issues that will impact on successful adoption and effectiveness of the deployment. It is important to note that the end goal of such research is not to replace care staff with technology, but to support them in their roles of helping their service users achieve their goals of becoming more independent. Accordingly, this paper presented the findings of seven one-on-one interviews with care staff who work with people with learning disabilities. This provides insight into the types of activities that their service users need assistance with, and within these activities, highlighting where most problems arise. It was noted that the key areas of support not only included help with completing activities of daily living, but also providing their service users with the ability to acquire key life skills, such as time management and relationship building. This research also explored the acceptability and appropriateness of off-the-shelf smart home sensors. The issues that emerged included the limited capability of service users in regard to understanding the purpose behind the technology, which in turn could negatively impact on their anxiety. We also explored how smart home devices could be incorporated into the support provided. This resulted in the care staff identifying different ways in these devices might be used in the context of prompting and guiding a person through ADL tasks, recommending personalised approaches to enhance their utility. Feedback on different types of activity-data visualisation techniques were related to specific suggestions for enhancing the format and representation of the data, as well as highlighting what data is critical and how would it be used. Furthermore, the research revealed the level of technical knowhow, proficiency and support backgrounds of the care staff, which presents interesting challenges for future care workforce skills development that will impact the uptake and prevalence of use of these emerging technologies. This also has implications for commissioners and funders of this technology to consider how they facilitate and plan for training, together with recognising how the smart home sensor data could be used, or even misused, and thus put in place safeguarding procedures. In relation to the latter, there would also be a need to consider what legal frameworks need to be in place where not just the autonomy and agency of the service user is preserved, but also the changing roles and responsibilities of the carers is accounted for.

This research shows how central engagement and relationships are given that this form of technology needs to learn from the user to personalise what it offers to them, and, importantly, how this learning needs to continue to be on-going as the service user's abilities and needs change over time.

A. Limitations and Future Work

This research was limited to care staff from a single institution. However, the intention of this work was to identify early stage requirements, opportunities and challenges for the development of assistive SH technology to support people with LD. The initial design requirements and recommendations presented in this paper can inform future investigations and development of assistive technology for people with LD.

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