Energising Health: A review of the health and care applications of smart meter data

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Foreword
Sacha Deshmukh
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I'm delighted to publish this report, which illustrates just how far-reaching and transformational the smart meter rollout has the potential to be.

The installation of smart electricity and gas meters in our homes is already creating a platform from which innovative new products and services can be built upon.

Now for the first time, this report sets out what this might look like in the rapidly advancing world of digital health and care, with potentially huge benefits for vulnerable groups in our population, and for us all.

While many of the ideas in this report are at an early stage of development, it's clear from the pace and direction of innovation in the health sector that the use of energy data will have a significant role in Britain's 'smart future'.

This is an exciting contribution and we're very grateful for the hard work of the team at UCL who have worked to produce this report.

Sacha Deshmukh
Chief Executive

Executive summary

Smart meters are being rolled out for the benefits they can bring to energy consumers and the energy system in Great Britain, but the data they produce may also be useful in health and care applications. This report examines what research, innovation and commercial activity has been conducted so far in this domain, and what the opportunities and challenges for its development could be. To do this we used a systematised review, and consulted with experts in the field.

Our review of the use of smart meter data in health and care applications presents a picture of a field in the early stages of development, but with big ambitions. A small number of research projects have presented evidence of the ability to use digital energy data to recognise activities or usage patterns that could be associated with a variety of health conditions. A number of companies also integrate such data into their health monitoring service offerings alongside other technology. As yet there is no clinical trial evidence of the effectiveness of using digital energy data to improve health outcomes.

Potentially recognisable health-relevant features include inactivity (such as through falls), sleep disturbance, memory problems, changes in activity patterns, low activity levels, occupancy and unhealthy living conditions. Much of the small amount of research in this area so far has been applied to Alzheimer's disease and dementia. Other key targets are a range of mental illnesses (such as depression) and care of people who are vulnerable in some respect.

Proposed applications include issuing alerts to carers when unusual activity patterns are recognised, and monitoring of things like the progress of conditions (to inform treatment needs) or of living conditions (such as use of heating or showers). We also raise the possibility of using digital energy data to inform diagnosis and public health, drawing parallels with initiatives in other areas, but there is no evidence at the moment that this will be possible or practical.

We identified a number of characteristics of smart meters that may prove particularly beneficial compared to other approaches such as wearable sensors and Internet of Things devices: their near-ubiquity (by 2020), low cost, versatility and provision of historical data. While these benefits lead to high hopes in some quarters to see health applications realised, there are also significant challenges. Considering user acceptance, we do not see many objections specific to smart meters as compared to other approaches. However, assurances around privacy may be important. While Smart Energy GB research shows smart meter privacy concern is low, sharing smart meter data with public services may be more controversial.

There are still advances to be made in more accurately recognising specific electrical appliances from dwelling-level data, which would increase the usefulness of smart meter-based systems in identifying activities and reduce false alarms. This could likely be improved if the sampling rate of energy data could be pushed beyond the current 10 second limit. Even if better activity recognition can be achieved, there is much more work to be done in reliably and usefully connecting observable energy use patterns with health conditions.

The manner in which smart meter data is stored and shared is tightly governed by regulation. However, using this data in health contexts is likely to involve taking it out of the regulated smart meter infrastructure to share it with third parties. Given the sensitive use to which such data will be put, ensuring good data security and privacy after data has left the currently regulated system should be an important focus for regulators considering its use in health contexts. The level of failure tolerance for health critical uses is also likely to be lower than for standard energy metering applications, with potential implications for how the system is regulated. Questions will also need to be considered about where responsibility lies when systems fail (with potential health consequences).

On the basis of our work we have a number of recommendations.

Research in clinical contexts
Clinical studies (based on rigorously designed randomised controlled trials) will be needed before the credibility of this approach begins to be established and considered in official guidelines.

More interdisciplinary work
The current locus of research in computing and engineering departments will need to expand to include researchers and practitioners working in health and care. There is already evidence of this being done, but new projects should consider this at the earliest possible stage.

Greater coherence
As well as reaching out across disciplines, the field should also endeavour to forge better internal linkages. Instruments such as workshops or conference streams could facilitate a more collaborative (or at least mutually aware) approach.

Novel use cases
We have included suggestions in the report for use cases which have not so far been proposed, at least in the published literature, including using smart energy data to inform diagnosis and for population-level analysis. There may be fruitful work to be done in scoping out these (and other) options further.

Focus on user acceptance
While we conclude that many user acceptance issues around smart meter data in health contexts are shared in common with other telehealthcare approaches, there should be an early focus on understanding what questions users (both practitioners and patients) might have.

Whole system approach
Research in this area is still at the stage of proving concepts. However, if smart meter health applications are to be used at scale they will be part of much larger smart metering and health data infrastructures. Early attention should be given to what system-level issues might be expected to arise and how they can be addressed.

Contents

Section 1

Chapter 1
Introduction

Great Britain (GB) is rolling out smart electricity and gas meters, primarily to bring improvements to the energy system such as accurate billing, reducing wasted energy, and better network management. However, the benefits could extend far beyond this. This report focuses on the potential they could have to contribute to one of the most important domains to both individuals and the state – the provision of health and care.
With an ageing population and medical advances allowing us to treat an increasing number of health conditions, the demands put upon the GB health system have never been greater. Health and care providers are increasingly looking to digital solutions to help provide care in a more personalised, responsive and cost-effective way.

The analysis of digital energy data from smart meters can give insights into activities within the home. It is this capability that leads to potential health and care applications.
With this report we have two key objectives, which are:

- to review examples of academic work and commercial developments in relation to the use of digital energy data in health and care applications.

- to explore the potential use of smart meter data in such applications, and recommend any further areas for research, collaboration and innovation where energy data could be used to realise positive outcomes for patients and health institutions.

To achieve these objectives we conducted a systematised review and consulted with experts in the use of digital energy data in health contexts, non-intrusive load monitoring (NILM), ambient sensing and digital health.

The report is broken into two sections broadly corresponding to the two objectives. In the first we briefly introduce smart meters, the smart meter rollout and some basics on how smart meters could be used to support health and care applications. We then provide an overview of previous and ongoing work, identifying unifying themes and areas of divergence.
In the second section we turn to consider the wider potential for use of digital energy data in health applications. This includes consideration of the range of the 'behavioural signatures' (behaviours which are known to be associated with certain health conditions) which may be detectable using energy data. We also explore the extent to which opportunities and challenges for digital health in general also apply to the use of smart energy data in this context, and what additional opportunities/challenges exist in this specific context. This discussion leads us to implications for research and regulation raised by the work.

Finally, as will become clear, one of our concluding observations is that there needs to be better integration between computing/engineering and health research to provide evidence that smart meter-based solutions are actually effective in a clinical context. We acknowledge that to many in the field of health, until such evidence is available, this topic will be of little practical use and may even appear to be a diversion from more pressing priorities. However, we believe there is sufficient evidence to merit further exploration of the potential (such as the Liverpool John Moores and NHS Mersey Care collaboration detailed in the next chapter). We have attempted to probe this potential as fully as possible, recognising that many of the applications considered may not ultimately be practical or even desirable. We hope this report can, at the least, widen the conversation.

Chapter 2
Smart meters and health applications: the basics

Smart meters

The smart meter rollout will see smart electricity and gas meters offered to more than 26 million homes in Great Britain by 2020.

Smart meters do the same job of measuring electricity and gas use as conventional meters, but with a number of additional capabilities. Central to their use in health contexts is the ability to transmit energy data automatically (rather than being read manually), and to record and share energy use at shorter time intervals.

Smart meters share data in a number of different ways. Figure 1 shows how the smart meter infrastructure is set up.

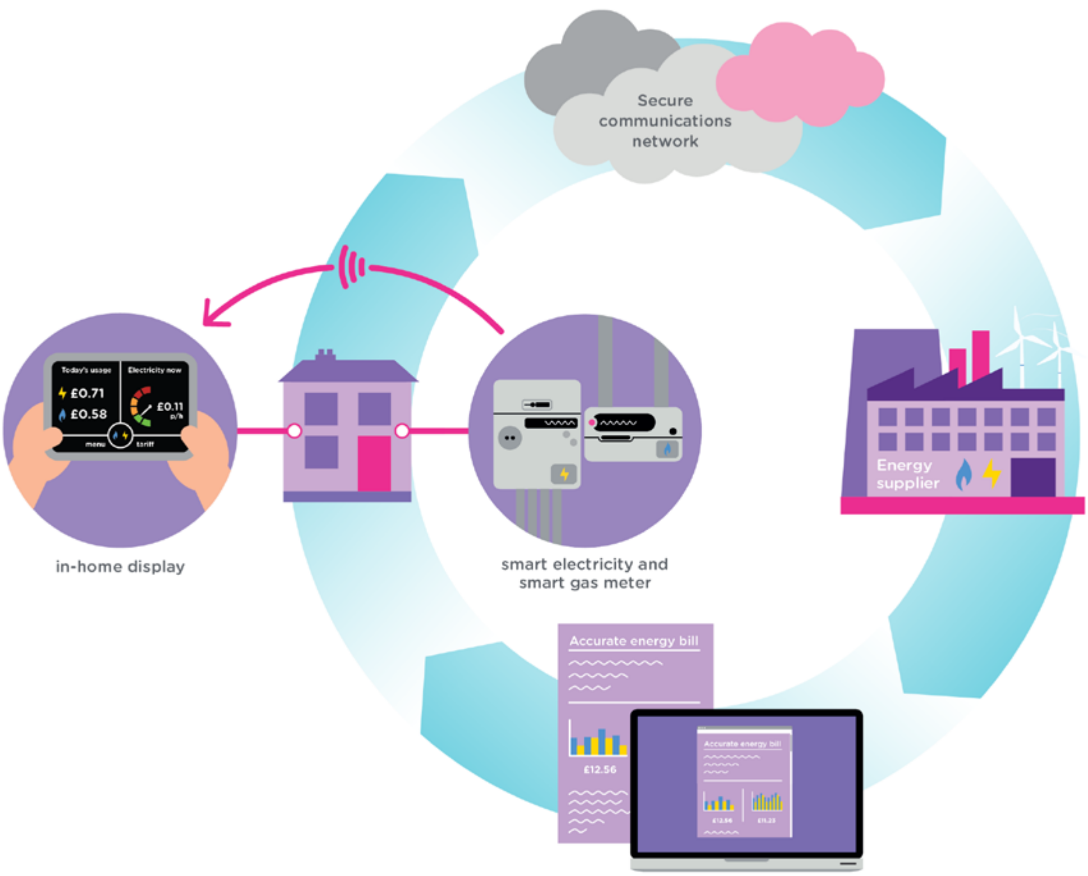


Figure 1. Basic flow of energy data in the smart metering system

The flow of smart meter data (and issues of data ownership, control and privacy) are considered in more detail in chapter 5. It is sufficient here to recognise that under current regulations, smart meters are capable of measuring electricity use approximately every 10 seconds and gas use every half hour, and transmitting this data in real time over the home area network (HAN) to a device which in turn can record and/or share it with third parties via the Internet. In particular, it is this electrical ‘load monitoring’ capacity that is the key to health and care applications[1].

Monitoring electricity use

At its simplest, smart meter data can be used to tell how much electricity is currently being used overall in a home, and what the patterns of use were in the past. More powerfully, however, it is possible to infer from the pattern of this overall data which specific appliances are being (or have been) used. This is known as non-intrusive load monitoring, see box 1.

Non-Intrusive Load Monitoring (NILM) is a method for identifying individual electrical appliance use from analysis of the current and voltage at the home electricity meter through analysis of electricity data sampled at frequencies around once every 10 seconds, up to hundreds of thousands of times per second. While NILM was first developed in the early ‘90s, academic interest in the field has increased rapidly since 2010, and commercial interest since 2014, both driven by an increased focus on energy demand in buildings combined with rapid reductions in the costs of sensing technology, and equally rapid improvements in the machine learning algorithms.

Whilst holding out a considerable promise, the full benefits of NILM have yet to be realised, because of the substantial challenges in distinguishing the signatures of individual appliances - particularly those with complex and user-variable settings and cycles like washing machines. There are, however, a number of commercially available systems capable of reliably identifying between eight and twelve individual electrical appliances in the home from their electrical signatures. NILM has the advantage that it does not require individual monitoring capacity to be built into each appliance, just the installation of one device at the meter (or a high specification smart meter), thus potentially significantly reducing the costs of understanding occupant behaviour as expressed through the use of appliances.

Box 1: Non-Intrusive Load Monitoring

1 There have in the past been discussions about whether smart meter infrastructure (as opposed to data) could support telehealthcare applications. This might include, for example, using the secure wide area network over which smart meter data is transmitted to also carry data from telehealthcare technologies. We are not aware of any plans to pursue this, and such applications are outside the scope of the work considered in this report.

The capacity to identify use patterns of individual appliances allows for a greater understanding to be developed of the behavioural patterns of occupants. Studying the use patterns (and changes in use patterns) of individual appliances offers the potential to detect abnormal patterns of behaviour linked to various health conditions. For example, unusual energy use overnight may be evidence that an occupant is experiencing sleep disturbances. Furthermore, analysis of the combination of uses of appliances, and variations in these, offers the potential to infer different forms of household practices which can then be linked back to a more nuanced understanding of the social purposes of that sequence of appliance use. Such combinations can be used to tell whether somebody is simply getting up in the night to go to the toilet, or whether they are getting up in the night to eat, make a cup of tea, and watch television for a period.

It is in interpretation of these ‘activities of daily living’ that the strongest potential of using smart energy data to support health and care lies. However, such applications would be just a small part of the much wider domain of digital health.

Smart meters and digital health

Digital health includes concepts such as the digitisation of health records, health data analytics, mobile health (mHealth) and wearables, and telehealthcare. The latter, which involves the provision of health and/or care services remotely, can be split into several sub-categories[2]: telemedicine (remote consultations, often using audio/visual equipment), telehealth (remote sharing of clinical data for managing long-term conditions) and telecare (remote provision of care).

It is to telehealth and telecare that smart meter data may be able to make a contribution, and for this reason we use the term ‘telehealthcare’ to describe the class of health applications to which the use of smart meter data belongs. Other examples of technology which fall under this classification would be personal alarm pendants, movement-triggered night-lights (for fall avoidance) and chair occupancy sensors. The benefits of telehealthcare are potentially many and varied, and can extend to patients, their relatives and carers, health professionals and the wider health and care system. Such benefits include reducing unnecessary hospital visits, reducing length of hospital stay by making returns home viable sooner, quicker recognition of adverse events at home, and reductions in burden on caregivers.

2 S. Stowe, S. Harding, 2010 Telecare, telehealth and telemedicine, European Geriatric Medicine, Volume 1, Issue 3, Pages 193-197 **http://www.sciencedirect.com/science/article/pii/S1878764910001087**

Chapter 3
Current work and the state of the field

By using NILM to recognise patterns and abnormalities in people's appliance use and activities of daily living, it may be possible to provide telehealthcare services without needing to rely on dedicated tools and sensors which may be costly and obtrusive. Indeed, since the vast majority of homes are expected to be equipped with smart meters by the end of the decade, such services could potentially be introduced with minimal expense and disruption to people's daily lives. However, there are also significant technical, social and regulatory barriers which would need to be overcome.

The next chapter provides an overview of research and innovation which is underway or has already been conducted in this field.

Our approach

One of the aims of this report is to summarise the current state of research and innovation in the use of smart meter data in health and care applications. To accomplish this we carried out a systematised review[3]. The review protocol, search record and list of final identified documents is available online[4], while the approach is briefly summarised in the Appendix to this report.

In total, our searches identified approximately 700 possibly relevant publications, of which just over 20 report work explicitly dealing with health applications of digital energy data. These documents underpin the current chapter. Further documents were identified which suggest health applications for their work, but did not set out explicitly to explore them – these feed into our consideration of wider potential later in the report. We also conducted a more exploratory review to inform the later chapter of the wider behavioural indicators of health conditions and costs to health services.

Through our review work we also identified a number of individual experts who are active in the field. Several kindly agreed to participate in brief semi-structured interviews to provide more detail on their work and views on potential for the field more generally. These discussions have also partly informed the remainder of the report[5].

3 Grant, M. J. and Booth, A. (2009) 'A typology of reviews: an analysis of 14 review types and associated methodologies', Health Information & Libraries Journal, 26(2), pp. 91–108. **http://onlinelibrary.wiley.com/doi/10.1111/j.1471-1842.2009.00848.x/abstract**

4 See **http://bit.ly/UCL-SEGB-health-protocol**

5 To promote free discussion we agreed not to attribute specific comments to named individuals, but several interviewees are included amongst others who have contributed to the report in the acknowledgements section.

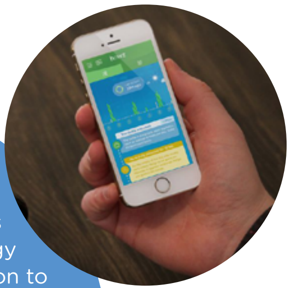
Overview of work

The use of smart meter data for health and care applications is an emergent field. All the papers considered here were published in the last decade, with the majority occurring in the last three years, which suggests the field is growing.

The relatively small number of academic studies is due in part to the field's recent development but also its specificity; it represents a novel application of smart meter data which was not necessarily foreseen or explored when smart meters were initially developed.

The studies come from a wide range of universities and institutions, most of which are situated in France, Germany, and the UK. On the whole, the research comes from computer science and engineering departments, since a central consideration of existing research is the application of algorithms which aim to process energy use and household sensor data. Notable exceptions are Norbert Noury who leads the Biomedical Sensor Group at the Institute for Nanotechnology at the University of Lyon, France and also the collaborative work led by Carl Chalmers (at Liverpool John Moores), described in box 3.

There are also contributions in the literature from private research institutions such as TATA Consultancy Service's innovation lab, IBM, Orange Labs and Toshiba. Commercial operations are more difficult to systematically assess, although we have identified several who are active in this area. A number of services use smart plugs or other forms of plug level monitoring, sometimes in combination with other sensors, to monitor occupants' use of specific appliances (or detect power outages) and raise appropriate alerts. These include 3rings[6], tekview Envirotxt[7], Cascade 3D Connected Care[8], KemuriSense[9] and CurrentCare (developed in partnership with IBM[10]). A whole-house monitoring system called Howz is described in the box.



Intelesant offers the 'Howz'[11] system which uses a clip-on whole-house energy monitor and load disaggregation to learn appliances use patterns, so that deviation from these patterns can be recognised and flagged with alerts in a smartphone app. The system is currently being tested in 100 homes as part of a testbed project with Surrey and Borders Partnership NHS Foundation Trust[12].

Box 2: Howz

6 https://www.3rings.co.uk/
7 https://tekview-solutions.com/envirotxt.php
8 http://www.cascade3d.com/connected-care
9 http://www.kemurisense.com/index.html
10 http://currentcare.uk.com/#system
11 http://www.howz.com/
12 https://www.newscientist.com/article/2121709-smart-meter-tracks-when-the-kettles-on-to-check-grandpas-ok/

Electricity utilities in Japan (TepCo) in conjunction with major multinationals (Hitachi & Panasonic) currently have field-trials underway to test the efficacy of the application of NILM approaches for assisted living. In the UK, the Energy Technologies Institute has filed patents for the application of NILM approaches to support Energy Management Systems that incorporate analysis of gas and water consumption alongside electricity. Such "multi-vector"[13] NILM approaches offer particular advantages to the understanding of occupant behaviour in homes. The simultaneous analysis of water consumption is of particular interest in the context of the provision of social care, as it has the potential to point to a significantly larger number of signature behaviours associated with health conditions.

Several ongoing research projects are notable for their potential to yield research outcomes in the near future. The University of Dublin's CLARITY Centre for Sensor Web Technology conducts research at the intersection of health, energy monitoring and ambient assisted living. One of the centre's research approaches integrates environmental sensors with electricity data[14]; another is a demonstrator of an integrated ambient assisted living test house[15]. The SPHERE research centre at the University of Bristol[16] is aiming to develop pattern recognition techniques for signatures of disease using data collected from domestic sensors which have not been designed with specific medical applications in mind. IDEAL at the University of Edinburgh[17] is investigating the extent to which feedback about energy usage influences consumption patterns.

While primarily aimed at energy demand reduction, the potential for positive health impacts of energy feedback are also under consideration.

13 Combining smart meter data with other data streams (e.g. on water usage) is referred to as 'multi-vector' NILM
14 **http://www.clarity-centre.org/content/smart-meter-environmental-monitoring/**
15 **http://www.clarity-centre.org/content/ambient-assisted-living-demonstrator/**
16 **http://www.irc-sphere.ac.uk/**
17 **http://www.energyoracle.org/**

What behaviours or conditions are being targeted?

There is no established way to classify the behaviours and pathologies targeted by smart meter health studies. We therefore take a pragmatic approach and examine the key themes.

The field's focus on 'activities of daily living' (ADLs) was referred to in chapter 2, and is reflected in the academic literature we consider here[18,19,20]. The concept was developed in the 1960s[21] as a means of tracking the diminishing range of daily tasks, such as cooking and washing, that a patient can perform as self-limiting conditions worsen. Changes in ADLs are cited as a means by which underlying occupant health conditions might be detected through changes in appliance use, or through detection by other sensors.

The work of Chalmers et al.[22] (see box 3) sets out an ambitious potential range of conditions which might be detected through smart meter data. ADLs, they argue, allow patterns of eating and sleeping to be determined, as well as changes in behaviour, routine and activity levels. Each of these changes may be relatable to memory problems, the decline of social relationships, the deterioration of personal hygiene and hyperactivity or inactivity. In turn, such changes may indicate Alzheimer's disease and other dementias, as well as other mental health problems.

18 Alcalá, J., Parson, O., Rogers, A., 2015a. Detecting anomalies in Activities of Daily Living of elderly residents via energy disaggregation and cox processes. Presented at the BuildSys 2015 - Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built, pp. 225–234. **http://dl.acm.org/citation.cfm?doid=2821650.2821654**

19 Clement, J., Ploennigs, J., Kabitzsch, K., 2012. Smart Meter: Detect and Individualize ADLs, in: Wichert, R., Eberhardt, B. (Eds.), Ambient Assisted Living, Advanced Technologies and Societal Change. Springer Berlin Heidelberg, pp. 107–122. **http://link.springer.com/chapter/10.1007%2F978-3-642-27491-6_8**

20 Chiriac, S., Saurer, B.R., Stummer, G., Kunze, C., 2011. Introducing a low-cost ambient monitoring system for activity recognition. Presented at the 2011 5th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, PervasiveHealth 2011, pp. 340–345. **http://ieeexplore.ieee.org/document/6038827/**

21 Katz S, Ford AB, Moskowitz RW, Jackson BA, Jaffe MW. 1963. Studies of Illness in the Aged The Index of ADL: A Standardized Measure of Biological and Psychosocial Function. *JAMA.* 185(12):914-919. **http://jamanetwork.com/journals/jama/article-abstract/666768**

22 Chalmers, C., Hurst, W., MacKay, M., Fergus, P., 2016b. Smart Monitoring: An Intelligent System to Facilitate Health Care across an Ageing Population, in: EMERGING 2016: The Eighth International Conference on Emerging Networks and Systems Intelligence. Presented at the Eighth International Conference on Emerging Networks and Systems Intelligence, IARIA XPS Press, Venice, Italy, pp. 34–39. **http://researchonline.ljmu.ac.uk/4680/**

Depression is mentioned by Ghassemian et al.[23] as a condition which their outline energy use monitoring architecture may be able to detect at its early stages, thus allowing for more effective treatment. Kalogridis and Dave[24] describe many examples of conditions which are detected using sensors, and the positive health benefits that detecting and reducing sedentary behaviours may have by reducing abnormal blood glucose levels. However, they also highlight that linking specific behaviours to conditions is difficult in practice. A sleep disturbance detection protocol is described by Chiriac et al.[25]. Further papers by the same authors[26,27], outline the structure of an ambient assisted living monitoring system and the progress of early lab testing, with the hope that the scheme will be extended to a trial of 100 homes. Sleep disturbance as a characteristic of Alzheimer's is also considered by Noury et al.[28]

The potential scope of behaviours and pathologies which may, in principle, be monitored using smart meter data is considered more generally in chapter 4.

Types of monitoring

There is a range of different ways in which digital energy data has been used in the research considered here. It is first important to note that none of the studies (or products on offer), so far as is possible to tell, use actual smart meter data in the monitoring they report. Instead they rely on either electricity monitors which clip on to standard meters and show whole-house usage, or plug monitors which record the electricity use of individual appliances. Clip-on monitors are the nearest proxy to smart meters as they provide whole-house measurements, and in terms of the frequency of data they can provide – higher sampling rates or appliance sub-monitoring would require installation of additional kit. Henceforth where we refer to 'smart meter data', this is used as shorthand for any digital energy data.

23 Ghassemian, M., Auckburaully, S.F., Pretorius, M., Jai-Persad, D., 2011. Remote elderly assisted living system - A preliminary research, development and evaluation. Presented at the IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC, pp. 2219–2223. **http://ieeexplore.ieee.org/document/6139911/**

24 Kalogridis, G., Dave, S., 2015. Privacy and eHealth-enabled smart meter informatics. Presented at the 2014 IEEE 16th International Conference on e-Health Networking, Applications and Services, Healthcom 2014, pp. 116–121. **http://ieeexplore.ieee.org/document/7001824/**

25 Chiriac, S., Saurer, B.R., Stummer, G., Kunze, C., 2011. Introducing a low-cost ambient monitoring system for activity recognition. Presented at the 2011 5th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, PervasiveHealth 2011, pp. 340–345. **http://ieeexplore.ieee.org/document/6038827/**

26 Chiriac, S., Rosales, B., 2012. An Ambient Assisted Living Monitoring System for Activity Recognition – Results from the First Evaluation Stages, in: Wichert, R., Eberhardt, B. (Eds.), Ambient Assisted Living, Advanced Technologies and Societal Change. Springer Berlin Heidelberg, pp. 15–28 **http://link.springer.com/chapter/10.1007%2F978-3-642-27491-6_2**

27 Chiriac, S., Röll, N., Parada, J., Rosales, B., 2012. Towards combining validation concepts for short and long-term ambient health monitoring, in: 2012 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops. Presented at the 2012 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops, pp. 268–274. **http://ieeexplore.ieee.org/document/6240404/**

28 Noury, N., Berenguer, M., Teyssier, H., Bouzid, M.J., Giordani, M., 2011. Building an Index of Activity of Inhabitants From Their Activity on the Residential Electrical Power Line. IEEE Transactions on Information Technology in Biomedicine 15, 758–766 **http://ieeexplore.ieee.org/document/5742702/**

The studies considered here also include examples in which smart meter data is complemented by other sensor data such as thermometers and accelerometers. For example, the field of ambient assisted living (AAL[29]) exists towards the more integrated end of this spectrum, and may or may not incorporate energy data. Indeed, Liao et al.[30] divides AAL approaches into two types: that which recognises behaviours using smart meter data alone, *and* those which are identified using a combination of smart meter data and other sensors.

While there is broad overlap between the work examined here and that of NILM we do not provide a comprehensive review of NILM here. Rather we summarise the field through figure 2 which shows, approximately, what appliances can be detected at different levels of sampling frequency. As suggested above, any analysis requiring a measurement frequency higher than the 7-10 second range requires an additional NILM device to be installed in the home.

Smart-meters also measure gas usage. However, our review did not return any items related to the health and care applications related specifically to gas usage. Neither do we address other utilities, such as water, although smart water meter data could conceivably be used to complement ambient monitoring approaches. While work has been conducted which relates water usage to occupant behaviours[31], this to be out of the scope of this review. We address the broader environment of potential uses of household energy data in chapter 4.

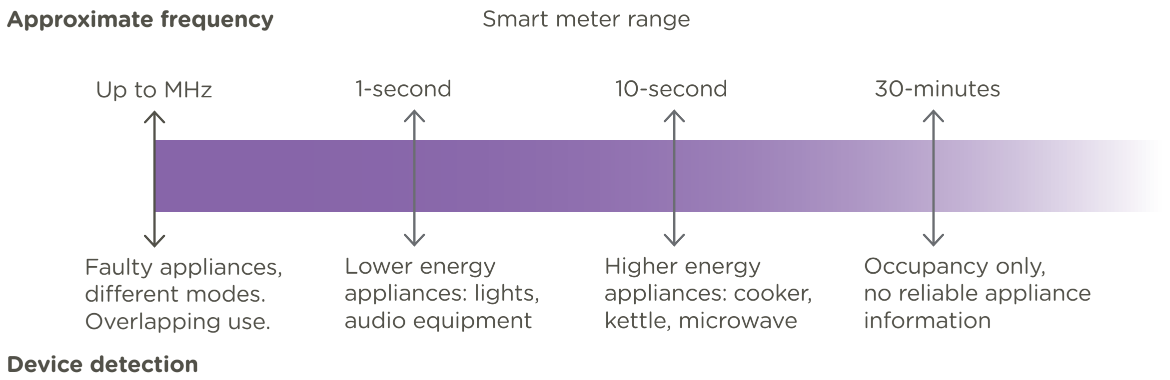


Figure 2. The approximate relationship[32,33] between the capacity of NILM to detect appliance and the sampling frequency. The relationship is complicated by whether both current and voltage are measured, as this allows active power to be determined. GB smart meters are able to measure energy use at least, 10 second intervals.

29 Calvaresi, D., Cesarini, D., Sernani, P. et al. 2016 Exploring the ambient assisted living domain: a systematic review J Ambient Intell Human Comput **http://link.springer.com/article/10.1007/s12652-016-0374-3**

30 Liao, J., Stankovic, L., Stankovic, V., 2014. Detecting household activity patterns from smart meter data. Presented at the Proceedings - 2014 International Conference on Intelligent Environments, IE 2014, pp. 71–78 **http://ieeexplore.ieee.org/document/6910429/**

31 Ghassemian, M., Auckburaully, S.F., Pretorius, M., Jai-Persad, D., 2011. Remote elderly assisted living system - A preliminary research, development and evaluation. Presented at the IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC, pp. 2219–2223. **http://ieeexplore.ieee.org/document/6139911/**

32 Nait Meziane, M., Picon, T., Ravier, P., Lamarque, G., Le Bunetel, J.-C., and Raingeaud, Y. 2016. A new measurement system for high frequency nilm with controlled aggregation scenarios. In Workshop on Non-Intrusive Load Monitoring (NILM), 2016 Proceedings of the 3rd International **http://nilmworkshop.org/2016/proceedings/Poster_ID23.pdf**

33 Chalmers, C., Hurst, W., Mackay, M., Fergus, P., 2016a. A smart health monitoring technology, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). **http://link.springer.com/chapter/10.1007/978-3-319-42291-6_82**

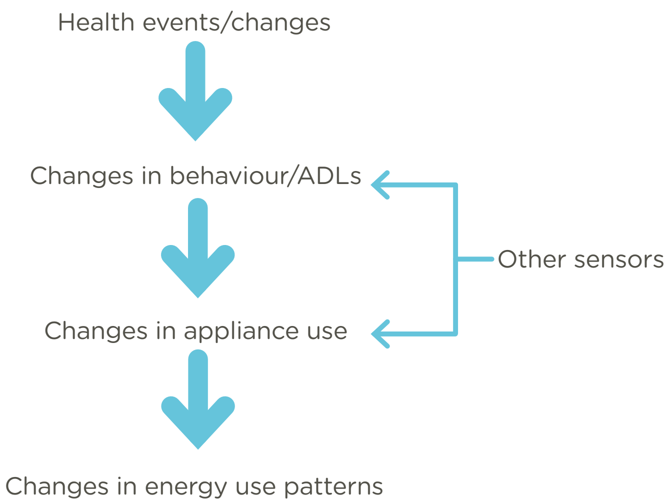


Figure 3. An approximation of the causal chain underlying smart meter health and care studies.

Several papers considered here describe wider infrastructural architectures required to integrate smart meters with home area networks, consumer access devices (CAD) and cloud computing facilities[34,35,36]. Since these do not have a direct impact on the types of health and care applications that are possible we do not consider this issue further. A general schema of the causal chain which underpins the approaches discussed here is given in figure 3.

Populations and samples

The context provided for almost all of the studies is the demographic projections in more developed countries which herald increased health spending due to population ageing. At this stage, several of the studies demonstrate `proof of concept' and do not use elderly participants directly. Noury et al.[37] on the other hand directly monitored 13 elderly people's electricity use over a period of nine months to understand their usage patterns and Chalmers et al.[38] used a random sample of energy use data of people aged over 70 drawn from a large Australian smart meter dataset (N=78,720). So far all studies have been based on small samples, with none exceeding 60 participants and the majority including less than 10.

34 Chalmers, C., Hurst, W., Mackay, M., Fergus, P., 2015a. Smart health monitoring using the advanced metering infrastructure. Presented at the Proceedings - 15th IEEE International Conference on Computer and Information Technology, CIT, pp. 2297–2302.
http://ieeexplore.ieee.org/document/7363385/
35 Chiriac, S., Rosales, B., 2012. An Ambient Assisted Living Monitoring System for Activity Recognition – Results from the First Evaluation Stages, in: Wichert, R., Eberhardt, B. (Eds.), Ambient Assisted Living, Advanced Technologies and Societal Change. Springer Berlin Heidelberg, pp. 15–28.
36 Bandyopadhyay, S., Ukil, A., Puri, C., Singh, R., Bose, T., Pal, A., 2016. SensIPro: Smart sensor analytics for Internet of things. Presented at the Proceedings - IEEE Symposium on Computers and Communications, pp. 415–421. **http://ieeexplore.ieee.org/document/7543775/**
37 Noury, N., Quach, K.A., Berenguer, M., Teyssier, H., Bouzid, M.J., Goldstein, L., Giordani, M., 2009. Remote follow up of health through the monitoring of electrical activities on the residential power line - preliminary results of an experimentation, Presented at the 2009 11th International Conference on e-Health Networking, Applications and Services (Healthcom), pp. 9–13.
http://ieeexplore.ieee.org/document/5406203/
38 Chalmers, C., Hurst, W., Mackay, M., Fergus, P., 2015b. Smart meter profiling for health applications. Presented at the Proceedings of the International Joint Conference on Neural Networks. **http://researchonline.ljmu.ac.uk/866/**

Analysis and measures of success

In order to detect the activities of occupants, and in turn understand if they change over time, the energy use data is typically disaggregated into specific appliance use patterns. As described above, higher energy use appliances are usually easier to detect. Appliances that have been focused on include kettles, cookers, microwaves, TVs, fridges and games consoles[39,40,41].

Algorithms play a central role in the literature in both categorising behaviours and detecting changes in it over time. While the intricacies of the various approaches are too many to detail here in full we give an overview.

Chalmers et al.[42] used an energy monitor at 1-10 second measurement frequency to train a device identifier, extracting a unique energy use profile for each device. From this data usage was categorised into abnormal and normal usage pattern using an automated process. Such device training processes are common in NILM and as the sophistication of NILM increases it is likely that a wider range of devices will be able to be detected with greater accuracy. In another work by Chalmers et al. they compare the ability of a range of different neural network algorithms at distinguishing normal and abnormal behaviour[43]. They find a success rate of over 90% for all the algorithms tested, with one as high as 99.2%.

39 Alcalá, J., Parson, O., Rogers, A., 2015a. Detecting anomalies in Activities of Daily Living of elderly residents via energy disaggregation and cox processes. Presented at the BuildSys 2015 - Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built, pp. 225–234. **http://dl.acm.org/citation.cfm?doid=2821650.2821654**

40 Kalogridis, G. and Dave, S. (2015) 'Privacy and eHealth-enabled smart meter informatics', in. 2014 IEEE 16th International Conference on e-Health Networking, Applications and Services, Healthcom 2014, pp. 116–121. doi: 10.1109/HealthCom.2014.7001824.

41 Song, H., Kalogridis, G. and Fan, Z. (2014) 'Short paper: Time-dependent power load disaggregation with applications to daily activity monitoring', in. 2014 IEEE World Forum on Internet of Things, WF-IoT 2014, pp. 183–184. doi: 10.1109/WF-IoT.2014.6803150.

42 Chalmers, C., Hurst, W., MacKay, M., Fergus, P., 2016b. Smart Monitoring: An Intelligent System to Facilitate Health Care across an Ageing Population, in: EMERGING 2016: The Eighth International Conference on Emerging Networks and Systems Intelligence. Presented at the Eighth International Conference on Emerging Networks and Systems Intelligence, IARIA XPS Press, Venice, Italy, pp. 34–39. **http://researchonline.ljmu.ac.uk/4680/**

43 Chalmers, C., Hurst, W., Mackay, M., Fergus, P., 2015b. Smart meter profiling for health applications. Presented at the Proceedings of the International Joint Conference on Neural Networks. **http://researchonline.ljmu.ac.uk/866/**

Chiriac et al.[44] draw a distinction between rule based and learning algorithms. The former is easier to implement, and are designed to detect individual events, based on particular criteria being satisfied, such as energy use dropping below a particular pre-defined level. Learning algorithms, on the other hand are considered by Alcalá et al. in their 'difference hidden Markov model', which they verify with plug level monitors. Clement et al.[45,46] use a `semi Markov' model in their detection of ADLs through appliance usage, but they compare it to an 'impulse model' finding that Markov approach cannot identify parallel ADLs as effectively as the latter. Another focus, as mentioned above, is the identification of abnormal or outlying data. Bandyopadhyay et al.[47] describe a general approach in this area which is applicable to smart meter data as well as other sensors.

Song et al.[48] also showed that the success of appliance usage detection depends on the characteristic of the algorithm used. For example, the cooker is identified with 62% accuracy under a time-dependent structure, but 77% under a time independent implementation. On the other hand, the fridge is less successfully identified under time independent implementation.

Noury[49] et al. produce "chronographs" of ADLs which are comprised of clusters of related activities. By contrast to the algorithm based approaches used in other studies, the correspondence between electrical usage and night time agitation was made by eye, in a way that they argue became intuitive for social workers involved in the study.

Measuring the success of a system depends largely on the proposed use case. For the work considered here, this includes either identifying unusual events to generate a notification, or monitoring changes over time to inform some aspect of care (the topic of possible use cases is expanded on in the following chapter).

As an example, the alarm system that Alacalá et al. describe monitors kettle activity and sends a notification when the kettle has not been used as expected[50]. Some of these alerts will be inappropriate, reflecting normal deviations from standard use rather than any health-related issue. The authors argue that for a recipient of the alert, such as a friend, relative or health care worker, getting an alert that turns out to have been nothing is not necessarily a problem and may actually be desirable for peace of mind. Clearly it would be a different matter if the use case were to be the automatic dispatch of an ambulance.

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44 Chiriac, S., Saurer, B.R., Stummer, G., Kunze, C., 2011. Introducing a low-cost ambient monitoring system for activity recognition. Presented at the 2011 5th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, PervasiveHealth 2011, pp. 340–345. **http://ieeexplore.ieee.org/document/6038827/**

45 Clement, J., Ploennigs, J., Kabitzsch, K., 2014. Detecting Activities of Daily Living with Smart Meters, in: Wichert, R., Klausing, H. (Eds.), Ambient Assisted Living, Advanced Technologies and Societal Change. Springer Berlin Heidelberg, pp. 143–160. **http://link.springer.com/chapter/10.1007/978-3-642-37988-8_10**

46 Clement, J., Ploennigs, J., Kabitzsch, K., 2012. Smart Meter: Detect and Individualize ADLs, in: Wichert, R., Eberhardt, B. (Eds.), Ambient Assisted Living, Advanced Technologies and Societal Change. Springer Berlin Heidelberg, pp. 107–122. **http://link.springer.com/chapter/10.1007%2F978-3-642-27491-6_8**

47 Bandyopadhyay, S., Ukil, A., Puri, C., Singh, R., Bose, T. and Pal, A. (2016) 'SensIPro: Smart sensor analytics for Internet of things', in. Proceedings - IEEE Symposium on Computers and Communications, pp. 415–421. doi: 10.1109/ISCC.2016.7543775.

48 Song, H., Kalogridis, G. and Fan, Z. (2014) 'Short paper: Time-dependent power load disaggregation with applications to daily activity monitoring', in. 2014 IEEE World Forum on Internet of Things, WF-IoT 2014, pp. 183–184. doi: 10.1109/WF-IoT.2014.6803150.

49 Noury, N., Berenguer, M., Teyssier, H., Bouzid, M.J., Giordani, M., 2011. Building an Index of Activity of Inhabitants From Their Activity on the Residential Electrical Power Line. IEEE Transactions on Information Technology in Biomedicine 15, 758–766 **http://ieeexplore.ieee.org/document/5742702/**

50 Alcalá, J., Parson, O., Rogers, A., 2015a. Detecting anomalies in Activities of Daily Living of elderly residents via energy disaggregation and cox processes. Presented at the BuildSys 2015 - Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built, pp. 225–234. **http://dl.acm.org/citation.cfm?doid=2821650.2821654**

In another use case, Noury et al.[51] gave computed ADLs to social workers to aid the monitoring of the progression of conditions, such as night-time activity related to the progression of Alzheimer's disease. There was an observed correspondence between the occupants reporting nocturnal agitation and the social worker's being able to visually identify the agitation from their electricity use record. Remote activity monitoring therefore provided an extra tool for the social worker to aid their understanding of the development of conditions. It is difficult to say to what extent greater or lesser accuracy would have been required to permit such a use.

Overall, it is evident from this review that there is currently no consensus as to how the success of determining occupant behaviours should be measured or compared even for particular use cases. This is in part due to the field being relatively new; several papers report the intention of increasing the size of trials and integrating the data with more measures of occupant behaviour such as plug level monitors. A consensus will likely only emerge when the field becomes more structured and (potentially) is subject to externally imposed compliancy regulations.

So far we have seen the health and care applications of digital energy data which researchers and industry are already investigating or employing. In the next chapter we move beyond this to consider the broader potential that smart meters may have in supporting people's health.

The work led by Carl Chalmers and conducted with colleagues at Liverpool John Moores' Faculty of Engineering and Technology has produced many of the papers considered in this review. The research has grown out of the existing expertise in machine learning and is being developed in collaboration with Mersey Care, a local NHS foundation trust.

Working with in collaboration with Professor of Primary Medical Care Chris Dowrick, the group is working with an Alzheimer's patient to monitor the progression of the illness over time using the system described in the main text. Initial feedback from health practitioners has been positive. The research outcomes will be available soon, and the group hopes the project will be commercially viable. More information about the collaboration is available on the Mersey Care website[52]

Box 3: Liverpool John Moores collaborates with NHS Mersey Care:

51 Noury, N., Berenguer, M., Teyssier, H., Bouzid, M.J., Giordani, M., 2011. Building an Index of Activity of Inhabitants From Their Activity on the Residential Electrical Power Line. IEEE Transactions on Information Technology in Biomedicine 15, 758–766 **http://ieeexplore.ieee.org/document/5742702/**

52 **http://www.merseycare.nhs.uk/knowledge-hub/mental-health-articles/smart-meters-study/**

Section 2

Chapter 4
Opportunities for smart meter data in health applications

In this chapter we look first at the wider uses digital energy data might find in the provision of health and care. This outline is guided by the existence of potentially recognisable symptoms, and costs to the health service. We then consider how this might sit within digital health more broadly.

What could smart energy data be used for?

Based on our review and expert interviews, we have identified a number of broad ends in aid of which it is possible smart meter data could (with appropriate consents) be employed. In each case we provide a brief illustrative example and suggest the relative readiness level, with the caveat that substantially more evidence is needed before even the most developed applications are likely to find wide adoption.

Alerting

Alerting relatives, carers or health practitioners to events which may require a response, such as when someone has been incapacitated by a fall. This functionality has already been the subject of research, such as in the work of Alcalá and colleagues as described in chapter 3[53], and tracking of electricity use is already built into systems such as those sold by CurrentCare, KemuriSense and Intelesant, suggesting that this development is relatively near readiness and is in the early stage of building evidence.

Monitoring

Monitoring patients on an ongoing basis. Such uses have been proposed by Chalmers and colleagues[54] and subject to exploratory research; applications include tracking:

- development of conditions by observing changes in recognisable behavioural symptoms with the aim of informing care (such as recognising progression of severity of Alzheimer's disease – see more detail below)
- treatments which might have side effects which cause recognisable changes in behaviour or energy use
- living conditions that may be connected with health conditions, such as personal hygiene (e.g. through shower use) or use of heating

Such ongoing monitoring is already an established part of telehealthcare so it is plausible that, if smart meter-based systems were shown to be effective, they could be employed in this context. However, there is currently only indicative evidence of their potential for use in this context.

53 Alcalá, J., Parson, O., Rogers, A., 2015a. Detecting anomalies in Activities of Daily Living of elderly residents via energy disaggregation and cox processes. Presented at the BuildSys 2015 - Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built, pp. 225–234. **http://dl.acm.org/citation.cfm?doid=2821650.2821654**
54 Chalmers, C., Hurst, W., Mackay, M., Fergus, P., 2016a. A smart health monitoring technology, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). **http://link.springer.com/chapter/10.1007/978-3-319-42291-6_82**

Aiding diagnosis

Aiding diagnosis through provision of information on behavioural symptoms that may otherwise be unavailable. This is not an application that has yet been proposed in research into health applications of smart meters, and there is no evidence that smart meters can add value in this respect. However, there are initiatives which are comparable in some respects.

For example, automatic testing for Parkinson's disease using voice characteristics has shown promising results[55], and to better inform this the Parkinson's Voice Initiative is aiming to collect voice samples from thousands of volunteers, just using smartphones[56]. it is possible that, in future, automatic voice analysis could contribute to diagnosis of that condition. It is conceivable (although there is currently no evidence to suggest this) that energy use signatures could provide contributory diagnosis data such as this in future – especially when considering that historical half-hourly data is routinely stored by smart meters.

Aggregate level analytics

Aggregate level analytics to identify prevalence and incidence of recognisable behavioural or building characteristics and their association with environmental or other factors, to inform public health initiatives. Work at UCL Energy Institute is ongoing to explore whether is it possible to infer how well insulated a home is using only smart meter data[57].

There has been pilot work in the NHS offering 'boilers on prescription' and insulation for people in cold homes[58]. In future, smart meter data could conceivably be used to inform targeting of such health interventions. In another hypothetical scenario, research has considered links between proximity to airports and insomnia[59], which in turn has been linked to other health conditions[60].

Such work currently relies on questionnaires. If sleep disturbances could be detected using smart meter data, it might be possible to construct insomnia 'heat maps' to inform transport planning or noise mitigation. Again, however, there is currently no evidence of this being attempted.

55 Bayestehtashk, A., Asgari, M., Shafran, I. and McNames, J. (2015) Fully automated assessment of the severity of Parkinson's disease from speech, Computer Speech & Language, 29(1), pp. 172–185. **http://www.sciencedirect.com/science/article/pii/S0885230813001149**

56 **http://www.parkinsonsvoice.org/index.php**

57 **http://www.lolo.ac.uk/wp-content/uploads/2016/04/Modelling-speaker-2-J-Chambers.pptx**

58 **https://www.theguardian.com/housing-network/2015/dec/03/sunderland-gps-prescribing-boilers-pills-warm-homes**

59 Kwak, K. M., Ju, Y.-S., Kwon, Y.-J., Chung, Y. K., Kim, B. K., Kim, H. and Youn, K. (2016) 'The effect of aircraft noise on sleep disturbance among the residents near a civilian airport: a cross-sectional study', Annals of Occupational and Environmental Medicine, 28, p. 38. **https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5009707/**

60 Floud, S., Blangiardo, M., Clark, C., de Hoogh, K., Babisch, W., Houthuijs, D., Swart, W., Pershagen, G., Katsouyanni, K., Velonakis, M., Vigna-Taglianti, F., Cadum, E. and Hansell, A. L. (2013) Exposure to aircraft and road traffic noise and associations with heart disease and stroke in six European countries: a cross-sectional study, Environmental Health, 12, p. 89. **https://ehjournal.biomedcentral.com/articles/10.1186/1476-069X-12-89**

As the review has shown, using smart meter data in health applications generally depends on identifying patterns (and changes in patterns) of energy use. Regardless of the precise method by which this identification is achieved, there are a number of general behavioural symptoms which smart meter data may be particularly useful in detecting. These may be used individually or in combination to contribute to any of the functions outlined above and include:

- inactivity (e.g. through falls, observable by absence of expected appliance use)
- sleep disturbances (e.g. unusual appliance use at night)
- memory problems or confusion (e.g. appliances such as stoves being left on unusually long)
- changes in other behaviour or activity patterns (e.g. mealtimes from observation of cooking appliances).
- occupancy/absence (e.g. longer periods of low energy use)
- low activity levels (e.g. where use of fitness equipment such as a treadmill forms part of treatment)
- unhealthy living conditions (e.g. if insufficient heating is used – which has been shown to exacerbate some health conditions[61] – or personal hygiene such as showering is neglected)

As the previous research reviewed in chapter 3 suggests, Alzheimer's and dementia have already been a target for researchers of health applications of smart meters. Whilst not being a diagnostic symptom, sleep disturbances are very common in dementia patients, affecting about 25–35% of patients[62]. One severe sleep problem is nocturnal agitation, which is also known as 'sundowning'. It is generally recognised as being a sleep disorder with the exacerbation of behavioral symptoms in the afternoon or evening, characterised by wandering and increased confusion which can lead to the person leaving their home, possibly also detectable using smart meter data[63].

Memory loss and confusion, also inferable from smart meter data (e.g. through stoves being left on), are additional symptoms of Alzheimer's and dementia[64], and the risk for falls is significantly increased in dementia patients[65]. NHS spending is highest for mental disorders, of which Alzheimer's is part[66], and the prevalence of Alzheimer's has been increasing (with Alzheimer's and dementia being the leading cause of death in England and Wales – see figure 4). Hence, the potential of smart meter data in contributing to health care is particularly large for dementia.

61 Jevons, R. C. Carmichael, A. Crossley, A. Bone, 2016. Minimum indoor temperature threshold recommendations for English homes in winter A systematic review. Public Health, 136, pp.4–12. **https://www.ncbi.nlm.nih.gov/pubmed/27106281**

62 Dauvilliers, Y., 2007. Insomnia in patients with neurodegenerative conditions. Sleep Medicine, 8, pp.S27–S34. **https://www.ncbi.nlm.nih.gov/pubmed/18346674**

63 Sleep disorders are also very common in Parkinson's disease, a neurodegenerative illness. See: Chahine, L.M., Amara, A.W. & Videnovic, A., 2016. A systematic review of the literature on disorders of sleep and wakefulness in Parkinson's disease from 2005 to 2015. *Sleep Medicine Reviews*. **https://www.ncbi.nlm.nih.gov/pubmed/27863901**

64 **http://www.nhs.uk/Conditions/Alzheimers-disease/Pages/Symptoms.aspx**

65 Van Doorn, C., et al. 2003, Dementia as a Risk Factor for Falls and Fall Injuries Among Nursing Home Residents. Journal of the American Geriatrics Society, 51: 1213–1218 **http://onlinelibrary.wiley.com/doi/10.1046/j.1532-5415.2003.51404.x/abstract**

66 **http://www.nuffieldtrust.org.uk/data-and-charts/nhs-spending-top-three-disease-categories-england**

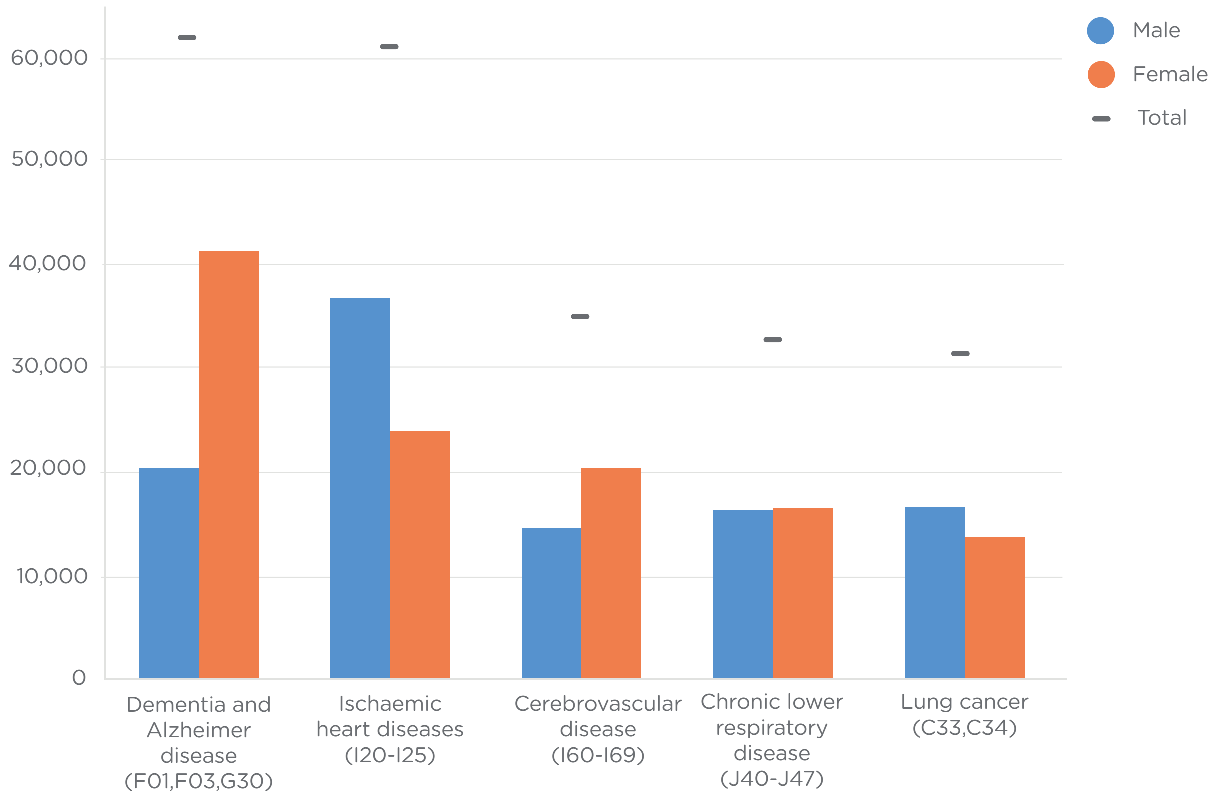


Figure 4. Registered deaths by age, sex and underlying cause in England and Wales, 2015 (Source: ONS)

Sleep problems are a symptom of a range of other mental disorders, including Common Mental Disorders (CMD) which encompass e.g. depression, anxiety disorders and phobias, and has a relatively high prevalence of 17%. Posttraumatic stress disorder (PTSD), mania, as part of bipolar or psychotic disorders, and attention-deficit / hyperactivity disorders are also all associated with sleep issues. Alcohol abuse is associated with a greater risk of fall[67].

In the elderly, a range of conditions could be monitored, such as falls or not heating the home adequately. Finally, it may be possible to detect either ineffective treatment or non-compliance with treatment for a range of conditions. Examples could include where medication which should reduce sleep disturbances is observed to be ineffective, or where the use of electronic medical devices can be monitored (where they do not already include direct communications capacity).

Table 1 summarises the range of identified conditions/vulnerabilities, and their associated behavioural symptoms that could be recognisable from smart meter data.

67 Adult Psychiatric Morbidity Survey: Survey of Mental Health and Wellbeing, England, 2014 [NS] **http://content.digital.nhs.uk/catalogue/PUB21748**

	Inactivity	Sleep disturbances	Memory problems/ confusion	Changes in other behaviour or activity patterns	Occupancy/ absence	Low activity/ non-compliance	Unhealthy living conditions
Dementia (including Parkinson)	✔	✔	✔	✔	✔		✔
Elderly	✔		✔	✔			✔
Anyone in need of home treatment						✔	✔
Alcohol abuse	✔		✔				✔
Common Mental Disorders		✔					✔
Post-traumatic stress disorder		✔					
Attention deficit hyperactivity disorder		✔					
Mania		✔		✔	✔		

Table 1. Summary of conditions that could be recognisable from energy data

Smart meters in the wider context of digital health

We have focussed so far on the role that smart meters may have in providing health and care service – but clearly this would be just one part of a much larger telehealthcare sector. The combined telecare and telehealth markets had grown to be worth over £1.7 billion globally by 2014, with the UK making up a quarter of the global telecare market[68].

The most significant growth in this broad sector is expected to be in the realms of mobile health (mHealth, including smartphone apps and wearable devices) and the connected home and Internet of Things[69]. As of 2015, smartphones were present in two-thirds of all households in the UK, while more than 80% of premises were able to access superfast broadband[70]. With this potential in mind, why might smart meters be of interest at all in the context of provision of health and care?

The important consideration here is the extent to which smart energy data is different to other approaches to telehealthcare, and what this means for how it might be expected to complement or compete with such technology. We see at least four key aspects to this.

68 Deloitte, 2015. Digital Health in the UK. **https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/461479/BIS-15-544-digital-health-in-the-uk-an-industry-study-for-the-Office-of-Life-Sciences.pdf**
69 Deloitte, 2015. Digital Health in the UK. **https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/461479/BIS-15-544-digital-health-in-the-uk-an-industry-study-for-the-Office-of-Life-Sciences.pdf**
70 Ofcom (2015). The Communications Market Report 2015.
https://www.ofcom.org.uk/__data/assets/pdf_file/0022/20668/cmr_uk_2015.pdf

Near ubiquity
If the smart meter rollout proceeds as planned, by the end of the decade the vast majority of homes in the UK will be equipped with smart meters. Smart meters should rapidly approach and exceed the penetration of smartphones, and are likely (at least in the short to medium term) to massively outstrip ownership of other connected home devices such as smart appliances. Furthermore, smartphone ownership in the over-65 age group stood at less than 20% in 2015[71] – and this is the age group most likely to benefit from telehealthcare services.

Low cost
While people will not necessary possess the consumer access device (CAD) necessary to convey the 10 second data necessary for NILM, such devices are likely to be inexpensive (in the order of tens of pounds). In addition, health applications will be but one motivator to acquire a CAD – people may also choose to acquire them in order to benefit from other services such as more advanced energy monitoring, demand response schemes (where people are given incentives to change their electricity consumption patterns), or home security. Of course, ongoing service provision is likely to also have a cost attached, but the highly automated nature of the analysis and alerting approaches that are being employed means this can also likely be delivered at minimal cost.

Versatile
As has already been highlighted, compared to some dedicated sensors (such as fall sensors), smart meter data has a relatively wide range of applications, based in part on its potential to monitor and respond to the use of many different appliances in the home.

Historical data
Dedicated telehealthcare technologies can only start monitoring once they are actually installed in the home. Smart meters, however, can give access to historical half-hourly electricity and gas data for 13 months before the point at which that data is sought (and potentially higher resolution if other energy monitoring services have been employed). This means that, for any home, there will already be a significant amount of data to inform pattern recognition algorithms or to allow investigation of the development of conditions or contribute to diagnosis.

It is clear that new telehealthcare services can only be relied upon to the extent that they have been shown to reliably improve health outcomes and avoid harm. More expensive dedicated systems are unlikely to be displaced where, for example, they allow individual-level monitoring or people who may need very rapid response to alarms.

In future, smart meters could form part of a wider smart home ecosystem where the potential health applications may not be the primary or even an intended use, but which allow easy repurposing for such applications. For example, smart thermostats such as the Nest are able to monitor and communicate the temperature and humidity in a dwelling. Both internal temperature and humidity are known to have associations with health[72], so the presence of such a smart thermostat (which can also detect occupancy) may then

71 Ofcom (2015). The Communications Market Report 2015.
https://www.ofcom.org.uk/__data/assets/pdf_file/0022/20668/cmr_uk_2015.pdf
72 Jevons, R. C. Carmichael, A. Crossley, A. Bone, 2016. Minimum indoor temperature threshold recommendations for English homes in winter A systematic review. Public Health, 136, pp.4–12. **https://www.ncbi.nlm.nih.gov/pubmed/27106281**

become part of a health monitoring ecosystem, complementing other ambient monitoring approaches including smart energy meters but also water meters, home security systems and many of the wide range of other IoT devices. Box 4 provides some examples of how such a data ecosystem approach is being used in the insurance sector.

As a hypothetical example of this approach, it is possible to see a role for smart meters data as a form of 'backstop' security. Smartphones and wearables rely on actually being carried with the person with a health condition to perform their functions. However, as we have seen, the kinds of condition which smart meter data may be useful in monitoring often involve memory loss or psychosis which could be associated with either forgetting to carry smartphones or wearables, or actively removing them. In such cases smart meter data will continue to be a source of insight and monitoring (so long as the CAD remains in use). Such a 'belt and braces' approach is made possible by the potential low cost of smart meter-based solutions.

Insurance companies have partnered with a number of Internet of Things companies to inform the pricing of insurance premiums. Vitality, for example, is currently selling the Apple Watch and Fitbit to health and life insurance customers so that customers can earn discounts (Vitality Points) on their insurance premiums for being healthy. One participating US based life insurer, John Hancock, provides customers with the Apple Watch for just $25 if the customer exercises regularly. The insurance policy also comes with a complementary Fitbit device which the insurer can use to track the customers' exercise habits and a third-party scheme called NutriSavings, which tracks people's food purchases via a loyalty card scheme. The insurer provides the customer with Vitality Points for undertaking these healthy behaviours which, in the following year, will contribute towards a Vitality Status, the highest of which rewards customers with a 15 per cent discount on their premiums.

Nest is partnering with insurance companies through its product Nest Protect, a smart smoke and carbon monoxide alarm. Participating insurance companies offer its customers Nest Protect (at no cost), which Nest claims will result in the insurer lowering the customers' premiums by up to 5%. According to Nest, this is because, unlike traditional smoke and fire alarms, because the Nest Protect is connected to the Internet, Nest can provide the insurance company with monthly updates on whether the device is operating (the batteries are charged, the sensors are working, the Wi-Fi connection is good).

These practices have been controversial in some quarters. Referred to as "price optimisation" (the practice of using non risk-based data such as shopping habits, occupation, marital status to inform the pricing of insurance policies in addition to the traditional risk-based data such as driving record) appears to have been made illegal in some US states.

Box 4: Insurance and the Internet Of Things

Chapter 5
Challenges

In this penultimate chapter we examine potential challenges to the uptake of smart meter-enabled health and care solutions, and consider the extent to which these are specific 'to that context of in common' with the wider telehealthcare domain. We consider user acceptance, practical and regulatory challenges separately, but acknowledging that they are highly interlinked. We use the final chapter to suggest areas for research and innovation in response to these challenges.

User acceptance

Clinician acceptance has been highlighted as an important (potentially the most important) factor in the uptake of telehealthcare[73]. Research has shown that clinicians may appreciate factors such as better, more frequent data, the ability to get al.erts and respond in a timely way to them, the ability to rapidly pick up when changes in treatment may be required (reducing the need for emergency visits) and identifying new clinical problems[74]. However, negative perceptions also arise associated with factors including[75,76]:

- not leading to expected relief of burden, for example by reducing number of visits but increasing number of phone calls
- reduced personal contact and the chance to build rapport with patients (which may also mean practitioners miss problems only noticeable in person such as personal hygiene, leading to patient safety concerns)
- the view that extra monitoring was unnecessary for good patient care
- concern around lack of formal instruction to use telehealthcare
- reliability and ease of use of technology, also leading to patient safety concerns
- introduction of additional procedures and the time and disruption associated with this
- changes to medical records documentation, increasing complexity
- data security concerns

It is possible that the ubiquity offered by smart meter-based health applications could play directly into some of these concerns, such as risk of growth in monitoring perceived to be unnecessary. However, we consider these to be mostly challenges which must be addressed in the wider field of telehealthcare and are not necessarily more applicable in the case of using smart meter data.

73 Wade, V. A., Eliott, J. A. and Hiller, J. E. (2014) 'Clinician Acceptance is the Key Factor for Sustainable Telehealth Services', Qualitative Health Research, 24(5), pp. 682–694 **https://www.ncbi.nlm.nih.gov/pubmed/24685708**

74 Lamothe, L., Fortin, J.-P., Labbé, F., Gagnon, M.-P. and Messikh, D. (2006) 'Impacts of Telehomecare on Patients, Providers, and Organizations', Telemedicine and e-Health, 12(3), pp. 363–369. **https://www.ncbi.nlm.nih.gov/pubmed/16796505.**

75 Brewster, L., Mountain, G., Wessels, B., Kelly, C. and Hawley, M. (2014) 'Factors affecting front line staff acceptance of telehealth technologies: a mixed-method systematic review', Journal of Advanced Nursing, 70(1), pp. 21–33. **https://www.ncbi.nlm.nih.gov/pubmed/23786584**

76 Brooks, E., Turvey, C. and Augusterfer, E. F. (2013) 'Provider Barriers to Telemental Health: Obstacles Overcome, Obstacles Remaining', Telemedicine and e-Health, 19(6), pp. 433–437. **https://www.ncbi.nlm.nih.gov/pubmed/23590176**

End users are either the patient being cared for, or non-professional carers (e.g. relatives) making use of telehealthcare solutions. Factors which have been shown to be important in their acceptance of telehealthcare include[77,78]:

- ease of use of the technology, and whether it is perceived as useful
- social influence, or the extent to which people believe others think they should use the system
- computer or technology anxiety and self-efficacy (for users who have limited experience of computers, which is more likely amongst older users – who form a large part of the target population for telehealthcare)
- perceived security, or the extent to which the system is perceived as being secure, private and reliable
- health professionals' recommendations
- social isolation

Again, many of these issues apply generally to telehealthcare initiatives rather than specifically to smart meter applications. It is possible that smart meter-based systems (that run invisibly in the background) will require little or no direct patient interaction compared to others involving dedicated technology that require more manual involvement to operate, making them preferential in respect of ease of use.

Privacy is an often-cited worry related to data-sharing in general[79], and assurance to the public on data privacy issues is an important consideration – for example, the smart meter rollout in the Netherlands was significantly delayed by a campaign around privacy concerns relating to the design of the Dutch smart meter rollout. Research by Smart Energy GB suggests that only 4% of people in Great Britain mention privacy as a concern in relation to smart meters[80]. However, using smart meter data in health contexts would require sharing data with new third parties, and potentially combining it with other sensitive datasets. As the public outcry over *care.data* indicates[81], communicating clearly what data is to be used for and how to opt in or out is likely to be key.

A further privacy challenge specific to smart meters is that, unlike most other IoT devices, smart meters remain attached to a premises and are inherited by each subsequent set of occupants. While the smart meter infrastructure and regulations include substantial safeguards around this, it will be important to ensure (and to reassure users) that any sensitive health data is not accessible in any way by anyone but the individual(s) for whom monitoring is ended.

77 Cimperman, M., Brenčič, M. M., Trkman, P. and Stanonik, M. de L. (2013) 'Older Adults' Perceptions of Home Telehealth Services', Telemedicine and e-Health, 19(10), pp. 786–790. **https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3787386/**
78 **https://www.hsj.co.uk/hsj-knowledge/downloads/telehealth-special-report-remote-control-of-care/5071580.article**
79 **https://home.kpmg.com/uk/en/home/insights/2017/01/data-this-time-its-personal.html**
80 Smart Energy GB (2017). Smart Energy Outlook, February 2017.
https://www.smartenergygb.org/en/resources/press-centre/press-releases-folder/smart-energy-outlook-february-2017
81 **https://www.publictechnology.net/articles/news/nhs-england-closes-controversial-patient-data-sharing-programme**

Technical (and associated practical) challenges

There are still a range of important technical limitations on the usefulness of smart meter data in health and care applications. One that has already been alluded to is the frequency with which energy data are made available by smart meters. While smart meters can provide data at up to 10 second intervals, systems which sample at a higher (e.g. sub-second) frequency have been shown to be able to infer appliance use with increased accuracy. This raises two questions – could smart meters provide higher frequency data and, if not, is it possible to perform more accurate NILM with 10 second data?

The frequency at which smart meters make energy data available are determined by the Smart Meter Technical Specifications[82]. This sets a minimum requirement, and while there is no reason to believe that suppliers would want to exceed this minimum standard, it is technically possible and, indeed, is simply a question of changing the settings in many existing smart meters. This is therefore a technical challenge that stems from regulation rather than fundamental technical limits. However, the flip side of receiving higher frequency data is that quantities of data soon become very large, presenting challenges for storage and analysis[83]. This is a problem common to all Internet of Things applications and, while unlikely to be an insurmountable barrier, will have impacts on costs of service provision.

Assuming that 10 second data is the best that will be available in the short to medium term, the challenge is then to develop better NILM. As has been previously suggested, this is currently an area of intense research interest and improvements in accuracy are likely, especially as more data for ground truthing becomes available[84].

Related to this is the question of to how to deal with the uncertainty that is always likely to be present to some degree in whether an action has been correctly detected, and even if it has, whether it means there is a genuine health concern or not. As Alcala et al.[85] suggest, the best response to this is likely to be a form of escalation procedure, whereby an alert is first sent to a relative or carer to check in with the patient and, if not response is received, more active measures such as a visit can be taken.

Even as NILM ability improves, there is still the issue that smart meter data shows energy use for the entire household. While approaches such as NILM can help distinguish the use of separate appliances, it is impossible at present for the activities of different individuals to be recognised (unless there are appliances which only one person uses). For some of the use cases already described, this is unlikely to be an issue. Indeed, recognising changes in behavioural patterns (such as a kettle unused at the normal time) is likely to be of most use precisely in cases of individual occupancy when there is no-one else physically present to notice such changes. However, this issue could pose significant problems for other use cases, such as monitoring compliance

82 SMETS Smart metering equipment technical specifications: second version **https://www.gov.uk/government/consultations/smart-metering-equipment-technical-specifications-second-version**

83 Illustrative figures suggest that, for a whole city, half-hourly smart meter data would require 400 Gigbytes storage, while 0.001s NILM data would require 400 Petabytes (**https://bristol-smart-energy.cse.org.uk/wiki/B:_Technical_-_Data_and_IT**)

84 That is, confirmatory data as to what activities were actually being undertaken

85 Alcalá, J., Parson, O., Rogers, A., 2015a. Detecting anomalies in Activities of Daily Living of elderly residents via energy disaggregation and cox processes. Presented at the BuildSys 2015 - Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built, pp. 225–234. **http://dl.acm.org/citation.cfm?doid=2821650.2821654**

with treatment, where the treated individual does not live alone. Nonetheless, as the capabilities of machine learning develop, it may be possible to detect unusual patterns of activity (such as overnight electricity use) despite the 'background noise' created by other individuals. Even today, it is possible that just recognising the unusual use of loads at certain times (such as an oven in the early hours of the morning) could be of assistance in multiple occupancy dwellings.

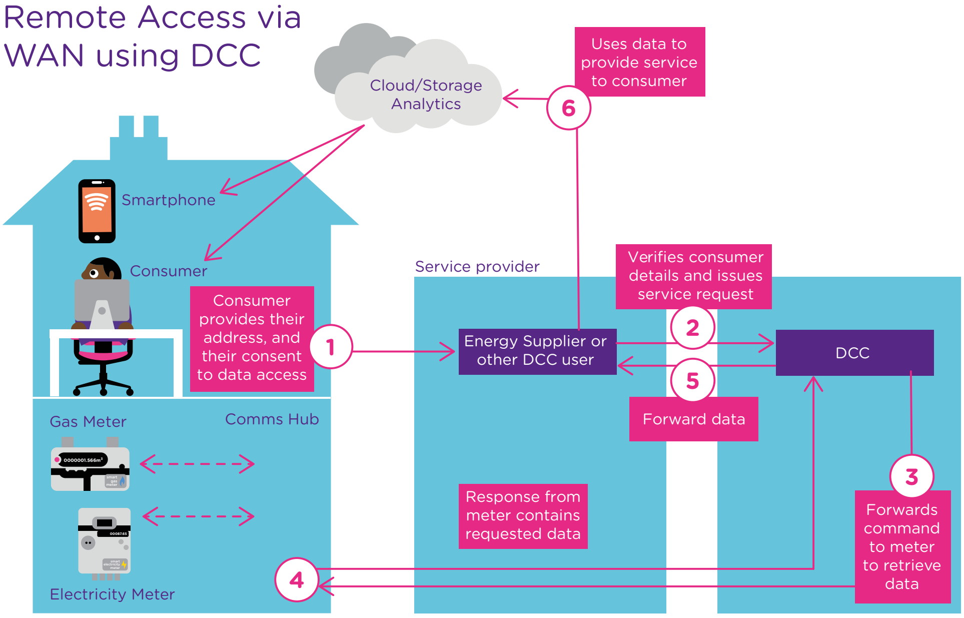
Regulatory issues

In this section we consider how the smart meter infrastructure is configured and overseen, and the questions that use of smart meter data in health applications raises for how smart meters are regulated. Smart meters themselves are subject to the Smart Meter Technical Specifications (SMETS), and stakeholders involved in the management of smart metering (such as energy suppliers, distribution network operators and other parties) are subject to the Smart Energy Code (the current version of which runs to over 2000 pages[86]).

Consideration of data privacy and security has been at the heart of planning for smart meters in GB, partly prompted by experiences in other countries such as the Netherlands where the smart meter rollout was delayed due to privacy concerns. The fact that energy data may be used in health applications reinforces the suggestion that such data can carry sensitive personal information.

It was decided for the GB rollout that smart meter data would actually be stored on the meter itself, and owned by the energy consumer (account holder/bill-payer). This data is communicated to the Data and Communications Company which passes it on to the energy supplier for that meter for the purpose of billing. By default this is daily data (i.e. the electricity/gas use in each day), but people may opt out to send only monthly data, or opt in to sharing half hourly data with their supplier (such as if they want to sign up to a time of use electricity tariff). The system is summarised in the diagram below.

Remote Access via WAN using DCC



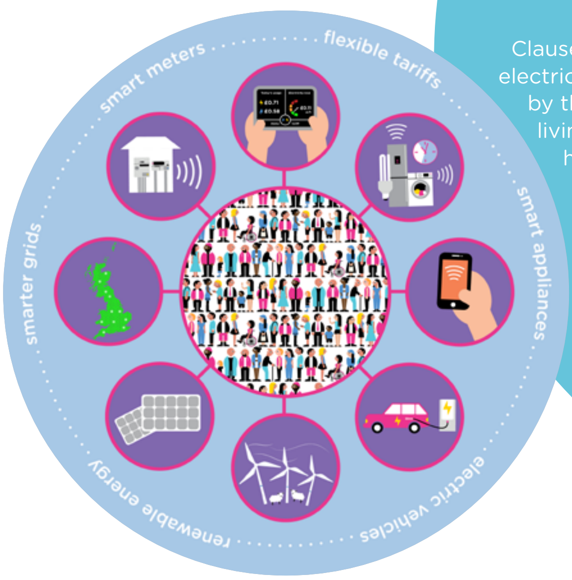
86 **https://www.smartenergycodecompany.co.uk/docs/default-source/sec-documents/smart-energy-code-5.4/sec-5-4---9th-february-2017.pdf?sfvrsn=4**

This data is communicated from the Home Area Network (HAN) to the Wide Area Network (WAN) and DCC Gateway with robust security protocols at every stage. Other organisations can request access to people's smart meter data via the DCC Gateway, but in such cases they must have explicit consent from the energy consumer, and be registered DCC Users with their activities tightly governed by the Smart Energy Code (SEC). It is therefore theoretically possible that an organisation could, with the user's permission, use data from the DCC to provide telehealthcare services. However, as discussed elsewhere in this the report, half-hourly (at best) data is unlikely to be of anything but the most crude use for such purposes. Furthermore, data may only uploaded from the smart meter to the DCC on a daily or even monthly basis (depending on organisations' preferences), making any kind of rapid response or notification impossible.

One area where it is possible to imagine DCC data being put to use is to inform health analytics at the population level. In such a case, it might be possible to analyse patterns in half-hourly (or even less frequent) data and identify associations with health-relevant data, either for individuals themselves or on a larger spatial basis. Again, explicit consent would be required from individuals in this way, and no suggestion has been found in this research of any plan to use smart meter data in this way. However, the Digital Economy Bill (see box 5) provides evidence of the will within government to make more effective use of this kind of dataset.

The Digital Economy Bill[87], which at the time of writing is at the report stage in the House of Lords, includes provisions about the sharing of personal data for the purposes of improving public service delivery. The conditions under which this can be done and restrictions of the nature of the data that can be shared are detailed at length and have generated extensive debate and a lot of controversy that we do not have the space to summarize here. However, we observe that key conditions for data sharing are when the objective is "the improvement or targeting of a public service provided to individuals or households", where this objective "has as its purpose the improvement of the well-being of individuals or households", which includes "their physical and mental health" (see clause 31 (8), (9) and (10)).

Clauses 32 and 33 explicitly discuss information disclosure to and by gas and electricity suppliers. Under the bill, information held by suppliers may be disclosed by them on the condition that disclosure "is for the purpose of assisting people living in fuel poverty in England and Wales or Scotland by ... (c) improving their health or financial well-being" (clause 33(2)). As explained in the main text, smart meter data is owned by the customer and all uses of data require specific opt-in consumer consent with the exception of monthly data for the purposes of billing. We have found no suggestion that this data could be eligible for sharing under the terms of any Digital Economy Act, but if it were then it may facilitate some forms population-level smart meter data analysis for health applications. There are also provisions under the bill for data sharing for research purposes, which could have a similar implication (although we note that under clause 61(4) authorities providing health services or adult social care are specifically excluded from this).



Box 5: The Digital Economy Bill

87 http://services.parliament.uk/bills/2016-17/digitaleconomy.html

Shorter interval energy data is available to people directly from the meter itself via the home area network (HAN). It is via this network that the in-home display (IHD) energy monitor gets the data to show near real-time (10 second) energy use, and via which a consumer access device (CAD) which might enable telehealthcare would also get access to this data. The HAN is subject to the same rigorous security controls as the WAN. However, once data is on the CAD and shared with third parties online, it is no longer a part of the formal smart metering infrastructure. Data security and privacy will, therefore, depend on the security employed by users themselves (such as for their wireless connection), Internet providers, and the third parties delivering the telehealthcare service. In theory, users can choose to share data via the CAD with anyone, and users will have to make a judgment as to how far they trust third parties to be who they say they are, to use their data as they say they will, and to store and transmit it securely and according to the Data Protection Act. This may be an area where further regulation will be required.

There is a related issue around reliability of the smart metering technology and data and communications infrastructure. As important national infrastructure, there are a multitude of robust standards governing reliability and accuracy. However, in the telehealthcare context the correct functioning of such equipment could, in some circumstances, mean the difference between life and death. If smart meter data should become widely used in health and care applications, there may be a case for regulation that also considers the health-related role of this infrastructure. However, such a situation is not considered likely in the short to medium term (at least).

Finally, there are considerations related to how research is conducted and evidence assessed in the fields of engineering/computing (where relevant research has so far mainly been conducted) and in health (where the application lies). Concerning research, the NHS research ethics requirements are substantially more stringent than those in other areas of research, for obvious reasons related to the protection of, and potential for harm to, patients and the public. A number of interviewees suggested that this had been a significant barrier to moving from testing of general potential to specific applications. Only when substantial evidence has been collected can organisations such as the National Institute for Health and Care Excellence (NICE)[88] begin to offer the guidance which is relied upon to inform health and care measures.

88 **https://www.nice.org.uk/guidance?unlid**

Chapter 6
Conclusions

Our review of the use of smart meter data in health and care applications presents a picture of a field in the early stages of development, but with big ambitions.

A small number of research projects, mainly based in university computing or engineering departments, have presented evidence of the ability to use digital energy data to recognise activities or use patterns that could be associated with a variety of health conditions. A number of companies also integrate such data into their health monitoring service offerings alongside other technology. As yet there is no evidence of the effectiveness of using digital energy data in a clinical context to improve health outcomes.

Current approaches use clip-on energy monitors or plug monitors, but the same techniques – mainly based around non-intrusive load monitoring and disaggregation with machine learning – could be applied to smart meter data. Health-relevant features that are potentially recognisable from smart meter data include inactivity (such as through falls), sleep disturbance, memory problems, changes in activity patterns, low activity levels, occupancy and unhealthy living conditions.

Much of the small amount of research in this area so far has been applied to Alzheimer's disease and dementia, which may include several of the above symptoms at various stages. Other key targets are a range of mental illnesses (such as depression) and care of people who are vulnerable in some respect. Proposed applications include issuing alerts to carers when unusual activity patterns are recognised, and monitoring of things like the progress of conditions (to inform treatment needs) or of living conditions (such as use of heating or showers). We also raise the possibility of using digital energy data to inform diagnosis and public health, drawing parallels with initiatives in other areas, but there is no evidence at the moment that this will be possible or practical.

The telehealthcare (comprising telehealth and telecare) market is projected to grow rapidly, especially through mobile health (mHealth), wearables and Internet of Things devices. Compared to these other developments, we identified a number of characteristics of smart meters that may prove particularly beneficial: their near-ubiquity, low cost, versatility and provision of historical data. We see a potential role for smart meter data in extending the provision of telehealthcare to cases where it may not currently be viable, in supplementing other ambient or dedicated solutions, or in time even replacing certain dedicated solutions – but in this case the evidence base will need to be much stronger.

While there are high hopes in some quarters to see such applications realized, there are also significant challenges, some of which are in common with telehealthcare in general, some of which are specific to smart meter-based solutions. From the user acceptance perspective (considering both practitioners and patients) we do not see many specific objections to using smart meter data as compared to other approaches. Potentially the main issue here will be around privacy. While Smart Energy GB research shows smart meter privacy concern is low, sharing smart meter data with public services may be more controversial. Indeed, there is already evidence of public disquiet about matching up health-related data as evidenced by the *care.data* controversy.

On the technical side, there are still advances to be made in more accurately recognising specific electrical appliances from dwelling-level data, which would increase the usefulness of smart meter-based systems in identifying activities and reduce false alarms. This could likely be improved if the sampling rate of energy data could be pushed beyond the current 10 second limit. Even if better activity recognition can be achieved, there is much more work to be done in reliably and usefully connecting observable energy use patterns with health conditions.

The manner in which smart meter data is stored and shared in tightly governed by regulation. However, using this data in health contexts is likely to involve taking it out of the regulated smart meter infrastructure (via a consumer access device) to share it with third parties. Given the sensitive use to which such data will be put, ensuring good data security and privacy after data has left the DCC system is likely to be a key concern of regulators considering its use in health contexts. The level of failure tolerance for health critical uses is also likely to be lower than for standard energy metering applications, with potential implications for how the system is regulated. Questions will also need to be considered about where responsibility lies when systems fail (with potential health consequences).

On the basis of this discussion we have a number of recommendations.

Research in clinical contexts
While there is growing evidence of the possibility of using smart meter data to recognise behaviours or activities associated with health conditions, but no published evidence of its use in actual clinical contexts. Only as such evidence (based on rigorously designed randomised controlled trials) becomes available can the credibility of this approach begin to be established and considered in official guidelines.

More interdisciplinary work.
The current locus of research in computing and engineering departments will need to expand to include researchers and practitioners working in health and care. There is already evidence of this being done (such as the Liverpool/Mersey Care collaboration), but new projects should consider this at the earliest possible stage. The inclusion of health specialists early on should also make it easier to navigate institutional ethics procedures that are currently a barrier to such research moving from general principles to clinical applications.

Greater coherence.
As well as reaching out across disciplines, the field should also endeavour to forge better internal linkages. Current work tends to be done in individual groups with little sign of collaboration or of common agreement on questions like measures of success. Instruments such as workshops or conference streams could facilitate a more collaborative (or at least mutually aware) approach. There is already more coherence around the field of non-intrusive load monitoring in general, and possibly within this context there could be forums to improve collaboration around health applications.

Novel use cases.
We have included suggestions here for use cases which have not so far been proposed, at least in the published literature, including using smart energy data to inform diagnosis and for population-level analysis. There may be fruitful work to be done in scoping out these options further, and there are likely to be many other novel use cases which can be conceived of.

Focus on user acceptance.
It is acknowledged that more work is needed to refine activity recognition from smart meter data. However, no work so far has focused on user acceptance. While we conclude that many user acceptance issues around smart meter data in health contexts are shared in common with other telehealthcare approaches, there should be an early focus on understanding what questions users (both practitioners and patients) might have. This can inform applications might ultimately be more acceptable.

Whole system approach.
Research in this area is still at the stage of proving concepts. However, if smart meter health applications are to be used at scale they will be part of much larger smart metering and health data infrastructures. Early attention should be given to what system-level issues might be expected to arise and how they can be addressed.

Appendix

Systematised review approach

To conduct the systematised review we first identified key concepts that we expected to appear in relevant work, such as smart meters, advanced metering infrastructure, load monitoring, health, care and medical. We then created search strings including variants of these concepts to search bibliographic databases including Scopus, Web of Science, PubMed and SciTech Connect. We employed 'wildcard' characters in the terms where, for example, a search for '*health*' would also capture words such as 'telehealth', 'ehealth', or 'healthcare'.

We augmented this database search with searches of Google Scholar and of Google, with additional searches including other relevant terms we encountered such as 'ambient assisted living'. Results which looked most likely to be relevant were saved. All the documents and web pages that we found were then screened for inclusion/exclusion on the basis of title/abstract/summary, with those that were included after this point being again screened on the full document.

Documents still included after this stage were worked through with information being extracted on points such as the type of digital energy data that was used, the data analysis methods, the sorts of appliances and activities that were considered, and their reported association with health conditions. We also worked through reference lists of these documents to pick up other publications not captured by the initial search.

In total, our searches identified approximately 700 possibly relevant publications, of which just over 20 report work explicitly dealing with health applications of digital energy data. These documents underpin the discussion in chapter 3. Further documents were identified which suggest health applications for their work, but did not set out explicitly to explore them – these feed into our consideration of wider potential later in the report.

Please see **http://bit.ly/UCL-SEGB-health-protocol** for the review protocol, search tracking table and list of included articles. There have in the past been discussions about whether smart meter infrastructure (as opposed to data) could support telehealthcare applications. This might include, for example, using the secure wide area network over which smart meter data is transmitted to also carry data from telehealthcare technologies. We are not aware of any plans to pursue this, and such applications are outside the scope of the work considered in this report.

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To find out more about smart meters please visit
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