Smart Future of Healthcare

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Acknowledgements

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Contents

Glossary

AAL	Ambient Assisted Living
ADLS	Activities of Daily Living
AHSN	Academic Health Science Network. AHSNs work with patients, industry and the health and care sector to enable the most effective digital solutions to reach more patients more quickly.
BEIS	The Department for Business, Energy and Industrial Strategy
CAD	Consumer access device: consumer-facing hardware that can provide almost real-time energy data from the smart meter
Clamp	Current clamp or current probe: an electrical device that clamps around an electrical conductor to measure current
DCC	Data Communications Company (Smart DCC): connects smart meters to energy suppliers, network operators and other authorised service users
EPC	Energy Performance Certificate
EU AAL	The EU Active and Assisted Living (AAL) programme, a European programme funding innovation that keeps people connected, healthy, active and happy into old age.
HAN	Home area network (HAN): facilitates communication among devices within the close vicinity of a home
HEMS	Home energy management systems
IoT	Internet of Things
NHSX	NHSX was founded in 2019 to drive forward the digital transformation of health and social care in the UK, allowing patients and staff to benefit from the latest digital systems and technology
NILM	Non-intrusive Load monitoring: a process of energy disaggregation where total power consumption is separated into specific loads according to electrical devices used in the home
SMETER	Smart Meter Enabled Thermal Efficiency Ratings
WAN	Wide Area Network: spans a large geographic area and often joins multiple local area networks (LANs)
Zigbee	An open global standard for wireless technology designed to use low-power digital radio signals for personal area networks

About the Authors

Dr Enrico Costanza

Enrico is Associate Professor in Human-Computer Interaction at the UCL Interaction Centre. His research lies at the intersection of design and technology and is influenced by behavioural and social sciences. His current focus is on interaction with AI and autonomous systems in everyday situations, and on systems that can help people make sense and take advantage of data (e.g. from the Internet of Things or from Energy Smart Meters), including interactive visualizations.

Enrico's research is related to sustainability and energy consumption, not only because of their societal and economic implications, but also for the opportunities that energy systems provide to study interactions with prototypes of future systems 'in the wild'. Before joining UCL in 2016, Enrico was a lecturer in Electronics and Computer Science at the University of Southampton. He holds a PhD in Computer Science from EPFL (CH), an MS in Media Art and Science from MIT (US), and an MEng in Electronics and Communications Engineering from York (UK).

Matt James

Matt joined 20/20health in 2012 and has particular interest in the intersection of health, values, technology and public policy. He relishes the opportunity to think about what it means to be human in light of technological change and innovation. His wide-ranging portfolio of expertise spans the arenas of public policy, academia and third sector, including previously working in Parliament as a parliamentary researcher for an MP.

Matt has co-authored reports on a wide range of topics including public health responses to obesity, reviewing post-transplant care for bone marrow transplant patients and reviewing the quality of care and models of best practice for those living with ankylosing spondylitis (AS). Committed to innovation in healthcare and the advancement of ideas through education, Matt is also an Associate Professor of Bioethics and Medical Law, an Associate member of the Royal Society of Medicine, a Senior Fellow of the Higher Education Academy (HEA) and a Fellow of the RSA.

Julia Manning

Julia is a social pioneer, writer and campaigner. She studied visual science at City University and became a member of the College of Optometrists in 1991, later specialising in visual impairment and diabetes. During her career in optometry, she lectured at City University, was a visiting clinician at the Royal Free Hospital and worked with Primary Care Trusts. She ran a domiciliary practice across south London and was a Director of the UK Institute of Optometry.

Julia formed 20/20health in 2006. Becoming an expert in digital health solutions, she led on the NHS–USA Veterans' Health Digital Health Exchange Programme and was co-founder of the Health Tech and You Awards with Axa PPP and the Design Museum. Her research interests are now in harnessing digital to improve personal health, and she is a PhD candidate in Human Computer Interaction (HCI) at UCL. She is also dedicated to creating a sustainable Whole School Wellbeing Community model for schools that builds relationships, discovers assets and develops life skills. She is a member of the Royal Society of Medicine's Digital Health Council.

Jon Paxman

Much of Jon's research at 20/20health explores ways of improving access, equity and outcomes within primary care. Research focus has included Personal Health Budgets, the UK's childhood immunisation programme, depression and mental health equity, obesity programmes worldwide, CFS/ME and whole-school wellbeing.

With particular interest in technology and sustainable healthcare, he worked on 2020health's independent evaluation of the 'Yorkshire and the Humber Regional Telehealth Hub' and contributed research to the 2013 NHS-VHA (UK/US) Digital Health Exchange Programme. He was later research lead on the Foresight Project Report, considering the future impact of technology on health, business, education and regulation in the optical sector. He has conducted more than 100 semi-structured interviews with clinical and strategic experts, led on survey design, facilitated FGDs and workshops with adults and children, and presented research findings at stakeholder round tables and launch events at Westminster.

Foreword

Smart meters are an essential digital upgrade to our energy system. They are the foundation for a more sophisticated, green and consumer-friendly energy system.

A smart energy system, underpinned by smart meters, is essential if we are to decarbonise our energy system and help tackle climate change. Smart meters are an important tool in supporting our energy system to work more flexibly and efficiently, making better use of clean, renewable energy and supporting consumers to reduce their energy use.

Smart meters also provide accurate bills and make energy use much more visible for everyone that has one. With millions of smart meters already installed in homes across Great Britain, it is vital that we start looking at the future potential applications for the smart meter network and the data it delivers.

Smart meters provide a great platform for new and innovative products and services to develop and thrive, such as electric vehicles, and in the field of health and care too. While many of the services are still in development or being trialled, it is extremely exciting to see the potential benefits of smart energy data in supporting our health and care system brought to life by this report.

We are very grateful for the hard work of the 20/20health team in carrying out this research. It is an important contribution to the ongoing development of innovation around incorporating energy data into health and care services.

Dan Brooke
Chief Executive, Smart Energy GB

Executive Summary

We are currently facing the greatest set of social, health and economic challenges since the Second World War. Before January 2020, the notion of a novel virus disrupting families, communities, businesses and economies worldwide was almost inconceivable. Even more so national lockdown, where members of the public, young and old, healthy and frail, are ordered to shut themselves away inside their houses and refrain from meeting family and friends (PMO, 2020).

We began this project in September 2019, several months before the advent of COVID-19. The subject we explore is of primary relevance to these uncertain times: how to use a burgeoning communications infrastructure to remotely monitor vulnerable members of society; how to recognise health deterioration as it happens and respond early; how to mobilise social capital and free up healthcare capacity; and how to keep families connected for peace of mind and wellbeing.

In this report we explore the possibilities of harnessing smart meter data in health and care monitoring systems. This is a research area of increasing interest given the rapid deployment of smart meters in a growing number of countries worldwide.

The opportunity for smart meter data analytics in health and care monitoring is in fact unprecedented, since never before has there been a government-driven roll-out of communications hardware into people's homes. If used as a health and care monitoring technology, the smart meter could soon become a virtually ubiquitous telehealthcare solution. No other ambient assisted living (AAL) or telecare technology comes close for scalability.

Three broad approaches to remote health and care monitoring using smart energy data are described in this report.

1. (a) Home monitoring for vulnerable individuals; (b) home monitoring as part of post-operative or restorative care

A growing body of research is demonstrating how energy usage patterns can be linked to health status, health changes and general wellbeing. The approach typically involves a process of (remote) non-intrusive load monitoring (NILM) of household electrical consumption, through which the use of various appliances, such as toaster, microwave, electric oven, kettle and washing machine, can be recognised. Machine-learning processes build a map of routine behaviours and activities over time, thereafter enabling computerised detection of anomalous behaviour or unexpected inactivity.

A person's deviation from normal routine may include the use of a kettle or other appliances during the night, possibly indicating sleep disturbances related to neurological deterioration, arthritic pain or mental health problems. The increase of energy consumption during late evenings and nights could suggest agitation, confusion and restlessness associated with 'sundowning syndrome', a symptom of dementia. Repeatedly forgetting to turn off the oven may indicate memory problems associated with mental health deterioration or mild cognitive impairment.

This type of monitoring approach could combine with gas and water usage data to give deeper insights on activities of daily living (ADLs). It could also be used in conjunction with other AAL technologies and in a variety of remote monitoring contexts, as shown in Table 1 below.

Table 1: Potential monitoring opportunities using smart meter data, primarily targeting single occupant households

Context	Service using smart energy data	Relevance (examples only)
Informal and formal care	Monitoring of vulnerable people	Frailty; Learning disabilities; Detection of early stage neurological disease
Health and social care	Monitoring of long-term conditions progression	Alzheimer's; Dementia; Parkinson's; Multiple sclerosis; COPD
Health care	Post-operative (rehabilitation) or post-discharge monitoring	Stroke; Heart failure; Hip/knee surgery; Vascular surgery
Health care	Impact monitoring of health intervention	Sleep medication; CBT; SSRI antidepressants; Physical therapy

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Health and care research using smart energy data and NILM remains early stage. The first clinical trial using the approach was conducted in 2016, a collaboration between Liverpool John Moores University and Mersey Care NHS Foundation Trust, in which two people with dementia were recruited for a six-month monitoring study. Following promising results demonstrating proof of concept (Chalmers et al., 2019), the team is now planning a 30-month study with 50 participants.

In Austria, Solgenium, a research, service and consulting firm, is likewise planning dementia research using NILM, combined with other easily accessible data, using the same principle of machine-learning techniques to inform clinical alerts and decision making. Solgenium has already tested NILM in a sleep study involving 25 participants to map sleep patterns and track the effectiveness of sleep medication, and funding for a second, larger pilot was recently announced.

In Japan, an informal care offering using smart energy data analytics has recently become a commercial reality, devised by the Sony spin-off (B2B) company Informetis and provided by the Tokyo Electric Power Company (TEPCO). The system automatically alerts family members to potential changes in the health or wellbeing status of elderly parents who live alone, often at some geographical distance, prompting a follow-up phone call or other action as necessary. As far as we are aware, this is the first service of its kind anywhere in the world. A commercial launch in Europe, following field trials, is planned for 2021.

Monitoring approaches involving appliance use recognition, most of which rely on extra equipment in the home for fast data sampling (e.g. at ten, one or sub-second intervals), are not the only smart energy propositions for AAL. Research from Sweden has explored the possibility of detecting deviations from daily routines from energy consumption alone, using aggregated 60 minute data – the kind routinely sent from smart meters to energy suppliers (e.g. Nordahl 2017 & 2019b). The UK health technology provider Howz and East Midlands AHSN are planning to test a similar approach in a forthcoming pilot in Leicester, supported by NHSX and Surrey and Borders Partnership NHS FT.

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2. Population-level screening and monitoring

An important area yet to be properly explored in health research is how smart energy data may be used by public health services to identify individuals and families at risk of fuel poverty and/or neglect, in winter months especially. Such conditions are often critical for older people and damaging to the health and development of young children. Studies have shown that energy efficiency measures that improve indoor temperatures are also associated with improved occupant health, notably cardiovascular, respiratory and mental health (Lima et al., 2020).

Energy consumption patterns revealed by smart energy (gas and electricity) data, analysed together with housing data and historical weather data over time, may provide enough information to enable the (entirely) remote detection of cold homes and unhealthy living environments. Insights could be further enhanced with the use of water usage data, and (though requiring supply or fitting) a smart humidity sensor in the home for the detection of damp living conditions. Any public service that screens and monitors individual households would of course require occupant consent.

Other opportunities to identify vulnerable households may come from metadata relating to low credit thresholds and emergency credit activation, which could be provided to local authorities at an aggregated level without consumer consent. Data may offer valuable insights on streets and districts where many might be struggling to meet need.

The energy sector could play an important role in population-level screening, given its existing responsibility to identify customers' potential vulnerability.

3. Self-monitoring for wellbeing and safety

Self-monitoring lies at the heart of smart home energy management systems (HEMS). These systems typically communicate through apps and are designed to make consumers more energy aware and give them more control over smart devices in the home. HEMS could facilitate consumer wellbeing and safety in a number of ways. These include:

- detection of unhealthy living conditions, triggering app-based messages and advice on keeping warm, or signposting to winter fuel help

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- recognising atypical behaviours indicative of health or wellbeing problems; app alerts could follow for self-help, or recommendations for health check-up
- detection of appliances left on, especially ovens; continued forgetfulness could be recognised by the system, with an alert generated to prompt follow-up with a GP

Despite the commercial availability of HEMS in some countries, wellbeing and safety opportunities of the technology have barely been explored.

System challenges and opportunities

The idea of using energy data within health or care monitoring systems is more than 10 years old. Slow research progress worldwide, particularly in clinical monitoring contexts, is perhaps in part due to government and institutional funders not recognising the specific multi-disciplinary requirements for rigorous clinical research involving smart energy data and machine learning. Without collaboration spanning computer science, engineering, energy and healthcare, studies remain only theoretical, with little evidence of real-world validity and scalability.

In terms of patient and clinician acceptance of remote monitoring systems using smart energy data, we have not identified major obstacles. In general, acceptance of any remote healthcare monitoring system is linked to health needs, together with robust privacy assurances and quantifiable realisation of benefits (Tsertsidis et al., 2019). The same should hold true for social care applications using smart meter data, particularly if these can support personal and family peace of mind, and community workforce productivity.

Acceptance issues related to population screening is another matter entirely. Remote screening via a ubiquitous technology never intended for such purposes would be wholly unchartered territory. Public health communication of how smart energy data are to be used would therefore need very careful consideration, especially to allay fears of surveillance, with opt-in and assurances on personal privacy vital for public trust.

The economic arguments for smart meter based telehealthcare would be strongly predicated on the pre-existing communications infrastructure. As a scalable technology, it could enable earlier detection of health risks and faster response

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to health events, reducing physical deterioration from delayed intervention. Reductions in hospital admissions or time spent in hospital by using smart energy data within a wider AAL monitoring solution is another cost saving opportunity. So too is the ability to enable individuals to live more safely and for longer in their own homes, avoiding or delaying expensive care home costs. Insights from smart meter data could, in time, inform clinical decision-making.

In contexts of informal and formal care, smart energy systems present opportunities to mobilise social capital by involving family members as 'first responders' to generated alerts. These systems could also enable workforce efficiencies, allowing community care workers to monitor individuals remotely and prioritise need.

Thinking about ways to harness smart meter technology is vitally important because our aging society indicates a future of much greater demand on health and care services, which in their current form are considered unsustainable (House of Lords, 2017). We are at the very beginning of a journey in the exploration of smart energy data possibilities. While the use of smart meter data in informal care monitoring is potentially imminent, government and institutional funders need to create much wider opportunities for cross-sector research, without which we may still be restricted to discussing important opportunities 10 years from now.

Recommendations

1. With the possibility of the use of smart meter data in telecare as early as 2021, Ofgem should review and ensure robust data security, privacy and consent (opt-in) regulations around the sharing of energy data with named third parties delivering care services and data analytics.

2. Ofgem should consider a requirement that named third-party telecare monitoring services using smart meter data register with the relevant property energy provider, regardless of data acquisition method. The energy provider should then ensure discontinuity of third-party access to smart meter data upon any changes in residency, to guarantee data protection of the new occupant(s).

3. The Department of Health and Social Care, NHS England, Office for Life Sciences and other institutional funders should support wider clinical

investigation of non-intrusive load monitoring (NILM) techniques within remote health monitoring systems. Funding opportunities need to target a range of neurological conditions with the aim of tracking disease progression, as well as post-operative and medical intervention home-monitoring.

4. Government, UKRI and other funders should consider ways to facilitate cross-sector innovation by creating research funding opportunities that explicitly link energy and health outcomes. Exploring opportunities to share data securely across existing research data portals such as the Smart Energy Research Lab (energy) and UK BioBank (health) would further facilitate cross-sectoral research.

5. Public-funded research should investigate how smart energy and smart water data may together provide deeper insights into activities of daily living and health risks associated with personal neglect. Trials need to involve families and carers, who are crucial to engagement and the mobilisation of social capital.

6. BEIS should consider wider societal applications of Smart Meter Enabled Thermal Efficiency Ratings (SMETER) technologies during its evaluation phase and dissemination of learning (January 2021). It should consider how these might scale as an alert, screening or monitoring solution for the detection of possible fuel poverty, neglect and poor living conditions that contribute to illness.

7. Supporting the Clean Growth Strategy, government and Smart Energy GB should consider public and media awareness campaigns to promote the importance of smart meters in tackling fuel poverty and health inequalities, given their potential to rapidly identify properties in need of energy performance upgrade (to Energy Performance Certificate (EPC) bands C or B). The campaigns should clarify the potential health benefits of a smart meter infrastructure, not just financial and environmental benefits.

8. BEIS should investigate one-second data sampling capability for future upgrades to smart electricity meter technology. Faster sampling rates may have potential to further increase home energy management engagement and facilitate remotely-activated health and care monitoring solutions without need for any additional hardware installation.

1. Introduction

Great Britain's official electricity and gas smart meter roll-out programme began in 2013 with the aim of making the technology standard throughout the country by 2020. As of 30th June 2020, there were 21.5 million smart and advanced meters in homes and small businesses in Great Britain, of which 17.4 million (31% of all meters) were operating in smart or advanced mode with remote communication (BEIS 2020a).

The 2020 deadline was ambitious, not least because there was and still is no legal obligation to accept a smart meter. Other reported barriers have included: poor Wide Area Network (WAN) coverage; problems maintaining generation one smart meter (SMETS1) functionality when changing energy suppliers (USwitch 2019); and difficulties of physical access to current meters (Bulb 2019).

And then came COVID-19. The impact of the coronavirus pandemic on the smart meter roll-out has been significant. Quarter 2 of 2020 saw only 135,000 smart meters installed, 850,000 less than in Quarter 1 (BEIS 2020a). The summer saw a period of installation 're-start' among most suppliers, while taking account of local lockdowns and the differing laws and regulations across England, Scotland and Wales.

In June 2020, the government published its response to the September 2019 consultation on the post-2020 policy framework for smart meters. Decisions announced included implementation of a four-year framework beginning on 1st July 2021 for non-domestic and domestic suppliers (BEIS, 2020b).

Irrespective of the uncertainties surrounding COVID-19 and its obstruction to rollout, the smart meter is set to become the standard energy metering device in people's homes. A nationwide smart meter infrastructure will create a more agile and resilient energy system, one that should enable us to take optimal advantage of renewable resources. It will also put an end to estimated billing and the inconvenience of manual meter readings (BEIS/Ofgem, 2018).

Smart meters can give almost real-time information on energy use and expenditure via an in-home display unit (IHD), meaning consumers can better manage their energy consumption, save money and reduce carbon emissions (Ofgem). The potential environmental benefits are indeed vital to the UK government's Clean Growth Strategy, which aims to reduce greenhouse gas emissions by at least 100% relative to 1990 levels by 2050 (CCC, 2019).

1. Introduction

The benefits of smart energy meters appear substantial, and recent research suggests these may extend further still.

In this report we review ways in which remote monitoring systems using smart energy data may offer valuable insights into the health and wellbeing of energy users. These users may be families struggling with fuel poverty and unhealthy living conditions; recently discharged patients requiring post-operative monitoring; or vulnerable people[1] who want to live independently and safely in their own homes.

Importantly, smart energy solutions have unparalleled scalability, given that the communications infrastructure and principal hardware – the smart meter – has government mandated roll-out and will very soon be commonplace in private homes and social housing across the UK.

Report structure

This report begins by describing the UK's current need for scalable health and care solutions and the contexts within which smart energy data has potential to help improve outcomes. In Section 3 we examine research and commercial activity in AAL using smart energy data. Our review principally considers possibilities using smart energy data alone and the communications infrastructure required to achieve monitoring at scale. We also explore how smart meter data may open up new opportunities for population-level screening and monitoring for unhealthy living environments.

Section 4 considers energy data analytics in combination with other AAL solutions; two case studies are included. Section 5 discusses barriers to scaling solutions using energy data from the perspective of research opportunities, technological challenges and public-facing issues.

Our conclusion summarises opportunities for the UK to support multi-sector collaboration and create the conditions for strong leadership in this unique domain.

1. As the report explores, categories of vulnerable people include the frail elderly and socially isolated, and those with learning disabilities or long term conditions.

1. Introduction

Methodology

Our review of smart energy data in health and care contexts builds on UCL's Energising Health report (Fell et al., 2017), which examined research, innovation and commercial activity in this domain, together with opportunities and challenges for development.

Using research protocols made available by UCL, we reviewed new publications of the last three years in health databases (Medline, Embase, AMED, DH-Data) and Google Scholar on the use of smart meter data in home energy management systems (HEMS) and in health and care contexts. Our review of commercial activity within the same fields was undertaken principally through Google searches; we also benefitted from signposting by experts during the project period.

To support our literature review we conducted a series of semi-structured qualitative interviews with academics, technology leads and entrepreneurs and AAL companies. Further information and opinion were obtained through email correspondence. A list of interviewees and correspondents can be found in Appendix B.

To explore ideas and system challenges yet further, we convened a two-hour, multi-disciplinary workshop at the London offices of Smart Energy GB, on 4th February 2020. Opinion from the workshop has informed this report, particularly with regards to challenges to the adoption and roll-out of monitoring solutions using smart meter data. A list of workshop participants can be found in Appendix A.

Finally, our project involved the oversight of a multi-disciplinary Steering Group, whose expertise, knowledge and impartiality helped shape the direction and content of this report. Their participation does not necessarily imply endorsement of the report's conclusions and recommendations. Steering Group members are listed in Appendix C.

2. In search of scalable, affordable solutions

Like many countries around the world, the UK has an aging society owing to simultaneous trends of declining birth rates and declining mortality rates (ONS 2019a). And while increased longevity may have brought more years spent in good health, it has also brought more years spent in poor health.[2] This has important implications for policy, because our aging society promises a future of much greater demand on our healthcare services, which in their current form are considered unsustainable (House of Lords, 2017).

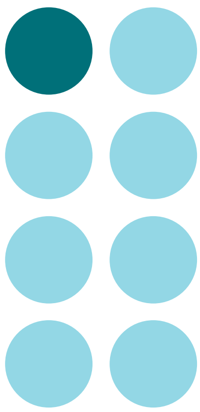
More than 24% of people living in the UK will be aged 65 or older by 2042, up from 18% in 2016

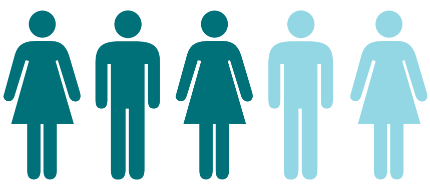
Source: ONS 2019b

We should also acknowledge the demands our care models place on unpaid, informal carers. These are often family members, who may have to combine work and other family commitments with caring for a spouse or parent. In the UK, one in eight adults are carers (around 6.5 million people), and three in five people are anticipated to become carers at some point in their lives (Carers UK, 2015).

In the UK
1 in 8
adults are carers

That's
6.5
million people



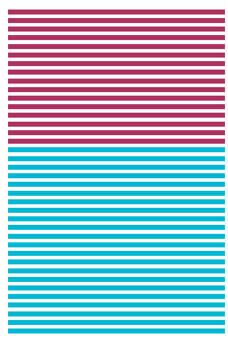


3 in 5

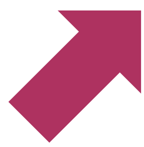
people are likely to become carers at some point in their lives

(Carers UK, 2015).

Around
3.8 million
people over the age of 65 live alone in the UK, of which
2.2 million
are over 75 *(ONS 2018a).*



Solitary living becomes increasingly likely in old age, and, in the next 20 years, the number of people aged 85 and over is expected to double.



2. At birth males in the UK can expect to live 16.5 years with a disability and females 20.9 years. Source: ONS, 2018. Health state life expectancies, UK: 2015 to 2017

2. In search of scalable, affordable solutions

Care for older people is a hallmark of a compassionate society. At the same time, research suggests that life satisfaction decreases as the number of hours spent caring increases: long informal care hours are not good for the carer, or the care recipient (Giusta et al., 2011).

Another great challenge for society is meeting the needs of the most vulnerable at a time when health inequalities are widening (PHE, 2018). Our social imbalances are leaving some families both fuel-poor and food insecure, which can have a profound impact on the health and wellbeing of children (BMJ, 2019). COVID-19 has simply further exposed health inequalities, with risk of serious illness higher among those living in more socioeconomically deprived areas, and among black, Asian and minority ethnic groups (PHE, 2020).

People living in the most deprived areas spend nearly a third of their lives in poor health, compared with only about a sixth for those in the least deprived areas.

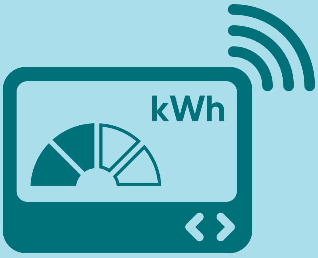
Public Health England, 2018.

The need for scalable, affordable health and care solutions is both great and urgent. NHS England's Test Bed Programme, launched in 2016, has brought together scores of partner organisations and innovators, and is testament to the fact that healthcare commissioning recognises not just the importance of digital innovation, but also how this must combine with pathway redesign for sustainable improvement.

To be scalable, solutions need to harness existing communications infrastructures and direct opportunities for capturing health-relevant data. Wi-Fi was not invented with the health and care of individuals in mind, yet Wi-Fi hardware and infrastructure are critical to many a commissioned telehealthcare solution. So often, it is the pre-existing technology that has made the new monitoring solution affordable.

If health and care monitoring systems can exploit the hardware and communications channels of the smart meter, they will have an important scalable opportunity. The smart meter may literally become a connected telehealthcare device, sitting in almost every home in the country. The extent to which proposed systems using energy data have demonstrated validity, application and scalability is the subject of this report.

2. In search of scalable, affordable solutions



Monitoring using smart energy communications in the UK

Before the advent of smart meters, scientists were already exploring how home energy monitoring might be useful to telehealthcare systems (Franco et al., 2008). By means of electrical circuit sensors and energy disaggregation techniques, the use of electrical devices and appliances in the home could be detected remotely, giving indication of the occupant's functional ability and wellbeing. Aside from initial equipment installation, the system would be completely non-intrusive.

Since the smart meter roll-out was announced in many countries worldwide, researchers have been exploring unprecedented opportunities in health and care monitoring using smart energy data – including approaches that might not necessitate a technician's visit to each and every monitored home.

In the UK, monitoring opportunities include using half-hourly data transmitted from the smart meter via the Data Communications Company (Smart DCC), revealing energy consumption patterns over time. Higher-resolution data can be achieved by using a consumer access device (CAD), capturing data from the smart meter at around 10 second intervals. This could enable the detection of high-energy appliances in almost real-time.

Even higher frequency (sub-second) sampling, using an current clamp or probe, is a further option, since this can in theory enable detection of low-energy devices invisible to a CAD, such as lights, hi-fi equipment, hair-dryers and televisions. Such technology is already being made commercially available in various smart home energy management systems (HEMS).

3. Health and wellbeing monitoring using smart energy data

Drawing from the literature, policy papers and project interviews and correspondence, we have identified at least six service contexts in which smart energy data may help provide useful, even critical, health and wellbeing insights:

1. **Monitoring of vulnerable people living alone**
2. **Monitoring of long-term conditions progression**
3. **Post-operative (rehabilitation) or post-discharge monitoring**
4. **Impact monitoring of medical intervention**
5. **Population screening for fuel poverty and unhealthy living conditions**
6. **Monitoring for self-care and home safety**

As we explore, most research into remote monitoring with energy data, whether in a social care context (1), health and care context (2) or purely clinical context (3 & 4), starts from a similar technological premise and aims to understand actions, behaviours and activities of daily living (ADLs) from the use of electrical appliances in the home. The solutions commonly involve high-frequency data sampling (10 seconds or less) and sit within the broad domain of ambient assisted living (AAL) (explored in Section 3.1).

Processes for population-level monitoring and screening (5) may not need the same level of data and detail, with half-hourly electricity and gas data possibly enough to provide useful indicators of fuel poverty and cold living conditions (explored in Section 3.2). Self-care and home safety (6), on the other hand, may see optimum benefits from higher rates of data sampling, and there are already commercially available home energy management services that could be developed to support this (explored in Section 3.3).

There is some potential overlap in technology use cases: a solution aimed at AAL monitoring may also have value at the population level; and a population-level solution may also have use within an AAL solution alongside other monitoring technologies.

It should be noted that many researchers have (to date) typically simulated the smart meter data channels of communication in their studies, aiming to see what can be achieved with low-resolution data (e.g. collection every 15 minutes or more) or higher-resolution data (10 seconds or less). Our discussion on

3. Health and wellbeing monitoring using smart energy data

data collection methods is mainly confined to the real-world communications hardware and channels required to see these types of solution at scale.

In these sections, we also discuss possible research and development synergies with the energy sector. Government and research funders have an opportunity to hasten progress and meet targets across both energy and healthcare domains at the same time. The opportunities are unique and they need to be fully recognised.

3.1 Ambient assisted living (AAL) solutions

3.1.1 Introduction to AAL

The domain of AAL seeks solutions of direct value to vulnerable and older people, their families and carers (EU AAL Programme, 2019). It is intended to protect or enhance peoples' health, wellbeing and independence, ideally in a way that is cost saving in formal health and care contexts.

Ambient assisted living monitoring typically includes three main technological components: hardware, comprising sensors and devices; data connectivity; and software, comprising a middleware management layer, data analytics and applications (Varnai et al., 2018). Data connectivity can be implemented through standard mobile networks (e.g. 3G, 4G) or Wi-Fi, or through more specialised radio networks developed especially for low-power devices such as sensors (e.g. LoRaWAN or NB-IoT), some of which are currently being deployed in the UK by both private companies and local authorities.[3]

Some of the most advanced AAL systems combine home sensors, smart plugs and wearables with machine-learning software to enable the remote monitoring of elderly or vulnerable people who live alone. By monitoring movements around (and in and out of) the home and the regular use of kitchen appliances, the system can infer and map behavioural routines and ADLs. Machine-learning algorithms

3. For example, see Diginomica, 2017: 'Bradford City Council, the Internet-of-Things and better public service.' https://diginomica.com/bradford-city-council-internet-things-better-public-service [Accessed 26 February 2020].

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are then used to identify any anomalous activity that could have relevance to health and wellbeing status. Unexpected inactivity may suggest incapacitation, while changes in movements or irregular use of kitchen appliances may be an indicator of memory problems, sleeplessness, mental illness onset or even disease progression (Enshaeifar et al., 2018; Lyu & Wolinsky, 2017). When anomalous behaviour is detected, an alert is automatically raised and sent to a family member, care worker, telehealth hub or clinician to respond and investigate.

In the UK, such monitoring systems are already found in informal care settings, through providers such as Howz, Canary Care, Kemuri Sense, Tynetec and Cascade 3d (see References). Formal commissioning of machine-learning AAL systems has also been seen in recent years, in both social and health care contexts. Commissioners are testing these systems to see how they might contribute to care pathway redesign in order to give better support to vulnerable people, both young and old, while maximising workforce productivity (2020health, 2020a). Specific clinical applications of AAL machine-learning technology are also being piloted, as seen in Bristol University's SPHERE Project[4] and the multi-site EU Gatekeeper Project.

3.1.2 Non-intrusive load monitoring (NILM) as an AAL solution

Academic and commercial research suggests, and to an extent has shown, that smart energy data can be used in similar AAL machine learning systems to enable remote monitoring and mapping of routines and ADLs.

The proposition typically starts with non-intrusive load monitoring (NILM), a process of energy disaggregation where total power consumption is separated into specific loads according to electrical devices used in the home. Most research in this area is in fact focused on the energy sector and NILM's potential value to consumers and the environment. High-resolution detail on home energy use may help energy providers better manage system demands, and motivate consumers to be more mindful in their use of energy resources, potentially reducing both their costs and carbon emissions.

4. SPHERE: Sensor Platform for HEalthcare in a Residential Environment. See: https://www.irc-sphere.ac.uk/about [Accessed 26 February 2020]

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Non-intrusive load monitoring (NILM): a summary

The concept of using NILM to determine the energy consumption of individual appliances dates from the 1980s (Hart, 1992). Its most common proposed application is for the disaggregation of energy bills, so that consumers can see appliance-related expenditure and take steps to reduce energy costs and carbon footprint. From a scalability point of view, NILM presents some complex problems that are not yet solved, even if the technology is now found in a few commercially available services. NILM therefore remains an active area of academic research.

The term NILM is used for energy data with different levels of temporal granularity, ranging from low-resolution data, where one sample is collected every 15 minutes or more, to high frequency data, sampled at up to 1MHz (i.e. one million samples per second). While high-frequency data can achieve high accuracy (detecting both high- and low-energy devices in the home), the data can only be obtained via additional hardware on the metering system, not directly from the smart meter, which has a temporal resolution only for one sample every 10 seconds (about 0.1Hz).

Various data processing and machine learning techniques have been applied to try and solve NILM for low-frequency data, ranging from Discriminative Sparse Coding (Kolter, 2010), to Hidden Markov Models (e.g. Parson et al., 2011), and more recently neural networks (e.g. Murray et al, 2019).

The success of current NILM techniques varies, based on the appliance that is being detected, which and how many appliances are available, and how many of them are used at the same time. For example, a recent study using data recorded at 0.16Hz (i.e. slightly higher than UK smart meters) reported correct detection of a microwave in more than 96% of instances, but only in about 74% for the washing machine (Xia et al., 2019). By contrast, with significantly lower-frequency data, at 0.016Hz, the results drop to 56% for microwave ovens and to 15% for washing machines.

Several datasets are publicly available to develop and test NILM algorithms. Unfortunately, these vary in terms of data recording frequency, as well as complexity (number of appliances and concurrent use).

In more general terms, the pace of NILM research is limited because data needed for the development of such algorithms derive from ‘intrusive load monitoring’ to capture appliance-level energy consumption traces. Such data can be costly and complex to collect, especially in comparison to other application domains where machine learning is demonstrating faster progress, notably in image recognition.

3. Health and wellbeing monitoring using smart energy data

The idea of using NILM to infer a person's domestic routines and ADLs, and hence support remote health monitoring, was put forward in 2008 through a collaboration involving Orange Labs, Grenoble University Hospital and the University of Grenoble (Franco et al., 2008), though very limited technical detail was disclosed about the operation of the system. The idea was then revisited in 2014 by researchers from Toshiba Research Europe Limited, based in Bristol, who linked it to the existing body of NILM research in other academic fields (Song et al. 2014). Centres of NILM health and care research have since included the University of Alcalá, Madrid (e.g. Alcalá et al., 2017a), and Liverpool John Moores University. Research emphasis in NILM has been on the detection of high-energy appliances, such as the kettle, toaster, microwave, electric oven and washing machine, since these are much easier to detect, common to most homes and frequently used.

The most important ADLs have been identified as bathing, dressing, eating and drinking, transfer in and out of chairs, walking and using the toilet (e.g. Lyu & Wolinsky, 2017). Clearly, not all ADLs can be inferred by energy usage patterns. However, with NILM capturing evidence of food and drink preparation, and also clothes washing, it assumes a certain level of mobility (i.e. of a single occupant) by these very actions. It can also map periods of expected daytime inactivity, where the occupant is regularly out of the house, for example at a weekly social event. Thus, even without additional AAL devices (e.g. movement sensors), NILM insights into routines and ADLs can be considerable.

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Figure 1 indicates how NILM would be used in much the same way as other AAL monitoring approaches that use machine-learning and automated alert systems.

Figure 1: Causal chain of events using NILM in AAL

Change(s) in health/wellbeing status

Changes in routines/ADLs

Changes in appliance use

NILM detection (events significant: Y/N?)

Alert generated

Response
(family member, social worker, telehealth hub, etc)

The use of NILM in health and care contexts is potentially extensive. It may not only provide opportunity for ongoing wellbeing monitoring, it may also be used to detect physical decline from a long-term condition, and even help assess the success of a medical intervention. Developing insights from Chalmers et al., 2016, and Ruano et al., 2019, Table 2 shows potential triggers for generated alerts in health and social care applications of NILM.

3. Health and wellbeing monitoring using smart energy data

Table 2. Inferred changes in routines and ADLs of older people living alone. High-energy appliance monitoring only.

	NILM detection	Potential behaviour/ ADL changes	Possible health or wellbeing risk/relevance (examples only)
Long term changes	Use of kettle or other appliances during the night	Sleep problems/ disturbances	• Mental health problems • Neurological deterioration • Pain associated with arthritis
	Later first use of kettle	Mobility problems/ sleep problems	• Neurological deterioration • Pain associated with arthritis • Deterioration in underlying disease
	Leaving appliances on (e.g. oven)	Memory problems	• Deterioration in mental health • MCI/dementia
	Appliance use at a time or on a day where previously there had been none	Decline in social relationships/ dropping out of activities	• Social isolation • Deterioration in mental health • Deterioration in underlying disease
	Stops using microwave and oven	Eating problems	• Indication of new condition (e.g. gastrointestinal) • Deterioration in underlying disease (e.g. cardiovascular disease/COPD/diabetes)
	Stops using kettle	Less intake of fluid (dehydration)	• Urinary tract infection • Falls • Exacerbation of cognitive impairment
	Decreased or irregular use of appliances	Difficulties performing ADLs	• Mental health problems • Cognitive impairment • Neurological problems • Deterioration in underlying disease • Worsening pain associated with underlying condition
	Increase of energy consumption during late evenings and nights	Agitation, restlessness and confusion	• 'Sundowning' syndrome (Alzheimer's/dementia)

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	NILM detection	Potential behaviour/ ADL changes	Possible health or wellbeing risk/relevance (examples only)
Short term changes	Later first use of kettle	Difficulty getting up in the morning	• Sickness/infection (e.g. UTI) • Increase in pain associated with underlying disease (e.g. arthritis)
	Stops using appliances altogether	Inactivity	• Fall/incapacitation • Sepsis • Acute deterioration from underlying disease (e.g. cardiovascular/COPD) • Stroke
	Sudden decrease in use of appliances	Lower capacity for ADLs	• Sickness/infection (e.g. UTI) • Deterioration from underlying disease (e.g. cardiovascular/ COPD) • Worry about falling • Failure to take prescribed medications appropriately • Adverse drug interaction

The utility of a monitoring system that only detects appliance usage depends greatly on the set habits and routines of the monitored individual. It is also important to recognise that none of the changes in behaviour listed in Table 2 necessarily signal health or wellbeing problems. Any alert generated simply invites follow-up (a text or a phone call) by a named contact, typically a family member in the contexts of informal care. At the very least this prompts contact between people who care about each other; in other cases the follow-up may provide opportunity for important early intervention on a health or wellbeing risk.

3.1.3 NILM and commercial Research & Development (R&D)

As discussed above, research to improve accuracy and scalability of NILM, for both energy efficiencies and health and care monitoring, is ongoing.

The Sony spin-off company Informetis has nonetheless launched NILM for informal care monitoring in Japan, in partnership with the energy provider TEPCO. The Japanese smart metering system is better suited to NILM services as it can sample at one-second intervals, as opposed to the 10-second sampling

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capability of the UK system. Informetis technology is thus able to detect not only high-energy appliances but also lower-power devices such as televisions. It then uses AI-driven data mining technology (its 'Metis App Engine') to visualise lifestyle patterns.

Its target users are family members who wish to monitor the wellbeing of an aging and often geographically distant parent.[5]

Informetis has a European R&D centre based in Cambridge, England. Exploring systems capabilities with the UK smart metering system, it has recently undertaken a social care pilot programme with Halton Borough Council and Halton Housing, in Cheshire. Six houses with single occupants were monitored, with a several-week machine-learning period informed by smart sockets placed temporarily in the homes. The sockets were then removed and an RCD (residual current device) fitted on the consumer unit to enable NILM. Named contacts for monitoring alerts were either family members or care workers, and in some cases both. The pilot was completed in 2019[6] and has been followed by further field trials in Europe. Informetis is planning a commercial launch in Europe in 2021.

Another company with intentions for the European (and UK) market is the Austrian research, services and consulting firm Solgenium, which considers ubiquitous smart meter technology as having clear advantages over conventional e-health technologies. Solgenium is primarily focused on clinical applications of NILM and is testing capabilities both as a stand-alone solution and in combination with gas, water and other accessible data. It is also examining the value of one-second interval energy data (normally requiring additional hardware in the home) and 15-minute interval data (automatically received by Austrian energy companies). Solgenium's data fusion and machine-learning processes are designed to give clinically relevant information directly to clinicians, or to generate automated clinical appointment messages based on detected changes in health status (2020health, 2020b). Partnering with Wien Energie (the largest regional energy provider in Austria) and several healthcare providers, Solgenium has future interest in identifying which clinical disciplines and patient conditions can benefit from NILM analysis and how this can contribute to greater levels of personalised healthcare. (See also Case Study below: SOLARIHS.)

5. For more information see company website: https://www.informetis.com/en/
6. Results of the pilot had not been published at the time of writing.

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Infrastructural advantages Solgenium is able to exploit include: (i) the single, national electronic healthcare record (ELGA), used by all healthcare providers; (ii) the integrated care model of health provision that incentivises an efficient patient journey and outcome; and (iii) the ubiquity of smart meters in homes across some of the Austrian federated states.

Case study: SOLARIHS (Solgenium)

SOLARIHS (SOLgenium Artificial intelligence-based Recognition of Indicators for Health Services) is Solgenium's approach to creating innovative AI-based tools for organisations, health professionals and patients utilising smart meter data.

The Austrian firm have reported promising results from a first pilot with 25 participants using NILM to map sleep patterns and also track the effectiveness of sleep medication, which may be prescribed due a variety of conditions (e.g. depression, burn out, neurodegenerative diseases). Collaborating with the energy provider Wien Energie and health experts from a sleep laboratory, Solgenium created a data set of one-second-interval smart meter data labelled with data from wearables and verified sleep diaries. Employing machine learning methods, Solgenium was able to create an AI model producing indicator results from 15-minute-interval smart meter data alone, which it considered on a par with wearable sleep trackers on certain sleep-health indicators. Interestingly, the pilot also suggested the one-second interval data to be an unnecessary requirement for this purpose.

During the summer of 2020, the firm secured 1.35m EUR in funding for a phase 2 SOLARIHS pilot, which aims to recruit at least 1,000 participants. The pilot will analyse a range of data sources, including electricity, gas, water and internet usage data, to test out the most clinically informative combinations.

Source: 2020health interview and correspondence with Solgenium, January, February & September 2020

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3.1.4 Dementia and smart energy data research in focus

Both moral and economic imperatives are driving research to improve quality of life and health outcomes for dementia sufferers. In 2015 there were an estimated 850,000 people living with dementia in the UK (Alzheimer's Society, 2014). Approximately 25% of hospital beds are occupied by people with dementia (Lakey, 2009); and while comorbidities are common with dementia sufferers, 20% of hospital admissions amongst this group are for preventable conditions (PHE, 2019).

Dementia costs the UK £26 billion a year. Two thirds of the cost of dementia is paid by people with dementia and their families.

Alzheimer's Society, 2014

Studies have claimed that earlier upstream interventions create cost savings downstream. A study from 2009 calculated that if 10% of care home admissions were prevented in England, savings by year ten would be around £120 million in public expenditure (social care) and £125 million in private expenditure (service users and their families), a total of £245 million (Banerjee & Wittenberg, 2009).

Another UK study, using 2007 costs, estimated that, over 10 years, early assessment and treatment could reduce health care costs by £3,600 per patient and societal costs by £7,750, in comparison with a scenario without early assessment and pharmacologic treatment (Getsios et al., 2012).

Dementia detection rates have risen considerably since the above studies were published, with around 540,000 people in the UK now diagnosed. But this still means that one third of people in the UK with dementia do not have a diagnosis (nearly one half do not in Wales), and around 1 in 3 people with a dementia diagnosis are not receiving appropriate NHS follow up support (Alzheimer's Research UK 2018; Age UK, 2018).

Dementia has been a focal point of smart energy data research using NILM. A service using NILM has three potential capabilities in supporting people with the disease:

1. **It may support early detection of dementia by recognising changes in routine behaviour and ADLs that link with important dementia warning signs, including forgetfulness, mood changes, apathy, confusion and difficulty completing normal tasks.**

3. Health and wellbeing monitoring using smart energy data

2. It may be used for remote monitoring purposes to allow people with mild to moderate dementia live safely and for longer in their own homes.

3. Systems may be able to detect dementia progression over time and thus support clinical review of medication and support.

Early detection of dementia (1) could derive from a telecare service aimed at supporting independent living. (It is unlikely that NILM would be used to support an otherwise healthy subject, at least in the foreseeable future.) Scenarios 2 and 3 are the subject of conceptual and clinical research and, if found effective and clinically useful, could see a return on investment.

The first in-depth clinical research of NILM in dementia care was undertaken by Liverpool John Moores University (LJMU) in collaboration with Mersey Care NHS Foundation Trust in 2016. This appears to have been the first clinical NILM study using recruited participants anywhere in the world (see below).

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First clinical monitoring study using smart energy data

In 2016, collaboration between Liverpool John Moores University and Mersey Care NHS Foundation Trust saw a first-of-its-kind study into dementia care support using smart energy data. Two people with mild to moderate dementia, under the care of Mersey Care FT, were recruited for a six-month trial. They both lived alone and had capacity to consent to the study.

It was a priority that the proposed NILM system should not require conscious interaction from the monitored individual at any stage. This was considered important for a remote service aiming to support people with dementia living alone, given the challenges they face due to memory problems.

Replicating the configuration of a smart meter with 10-second data capture, the system was able to identify the unique energy signatures of the kettle, toaster, microwave, cooker and washing machine. Patterns of appliance use were identified to infer ADLs and routines (using the Bayes Point Machine binary classifier).

A 40-day machine learning period was implemented prior to the system becoming operational for the trial. The system framework operates in three specific modes:

1. **Mode 1** (device training): power readings are obtained from the patient's smart meter and recorded in a data store. Readings are used to train the system to identify device signatures from aggregated load readings. The training process achieves this using machine-learning classifiers.
2. **Mode 2** (behavioural training): data features are extracted to identify normal and abnormal patterns in behaviour. The features allow the system to recognise the daily routines performed by patients, including their particular habits and behavioural trends.
3. **Mode 3** (prediction mode): the detection of both normal and abnormal patient behaviours is conducted in real-time. During this process, the monitoring application interfaces with web services to receive real-time monitoring alerts about the patient's wellbeing.

The system was designed to capture any deviation from routines that might signal potential disease progression. For example, a person with dementia may exhibit an increase in certain behaviours in the late afternoon or early evening, caused by agitation, restlessness and confusion. Often referred to as sundowning syndrome, symptoms may be recognised by gradual changes in energy usage over long observation periods.

Throughout the six month trial, routines were detected and a total of four sleep disturbances were observed, with anomalous activity including kettle and toaster use between midnight and 5am. This kind of behaviour change observed over a longer period – potentially with increasing frequency – could give clinicians important insights into the speed and progression of dementia.

Sources: (1) Chalmers et al., 2019. (2) 2020health interview and correspondence with Dr Carl Chalmers and Dr Paul Fergus, December 2019

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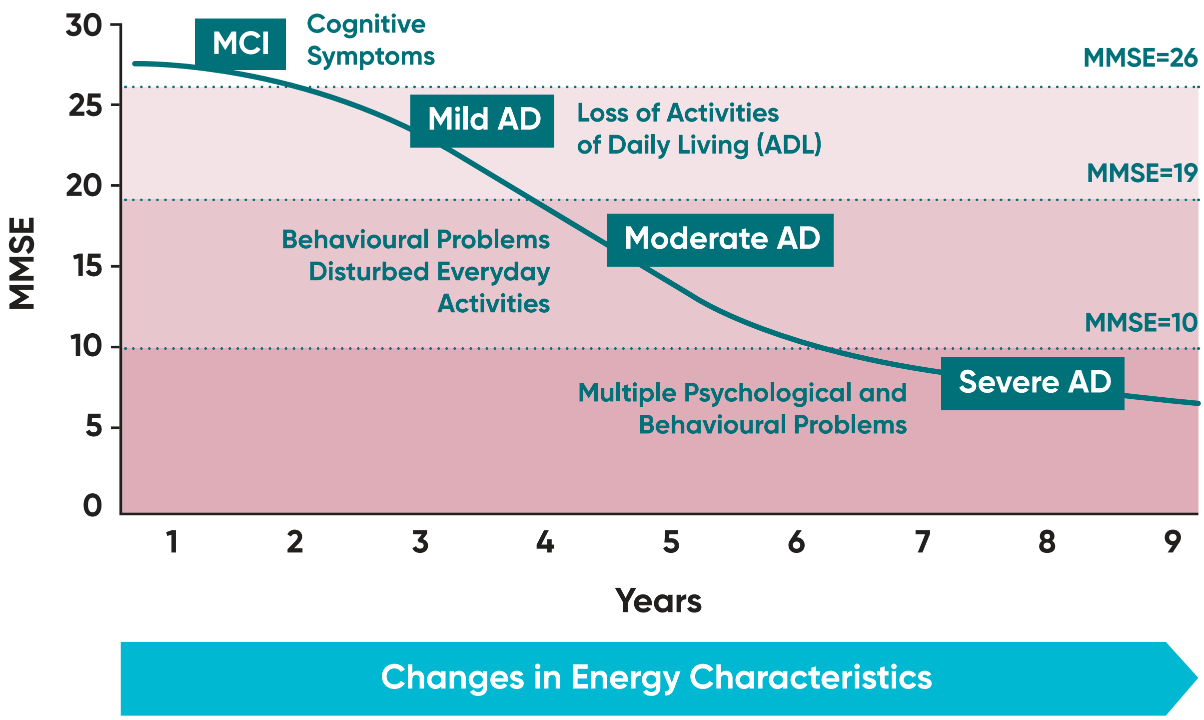
Figure 2: Relating changes in energy use patterns to the MMSE Framework. Source: Liverpool John Moores University (Chalmers et al., 2019).



The next step for LJMU and Mersey Care is a larger, longer-term trial with 50 patients monitored over a period of two and a half years. One challenge is to demonstrate consistent performance of NILM algorithms across different households. Another is to see whether changes in routines and ADLs can be somehow linked to the score of the Mini Mental State Examination (MMSE), a cognitive screening test commonly used by clinicians in diagnosing and staging severity of dementia (see Figure 2). If so, evidence from NILM may in the future support clinical decision-making on patient support.

The Austrian firm Solgenium (introduced above) is likewise planning NILM research into dementia with a major Austrian energy provider and several healthcare organisations. Delayed by the COVID-19 pandemic, the pilot aims to recruit 500 participants and use NILM in combination with other accessible data sources, using the same principle of machine-learning techniques to inform clinical alerts and decision-making.

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In the future, NILM may become just one important component of a broader clinical AAL monitoring solution for dementia care. But for now, research needs to establish the extent to which NILM as a scalable, stand-alone energy monitoring technology can provide clinically useful insights into people's behaviours and ADLs, ideally without or with minimal supply and fitting of additional hardware in the home.

3.1.5 Configuring a scalable system for NILM

The scalability of any NILM solution relates to technical costs and the ease of building on existing communications architecture.

Electricity and gas data from smart meters are sent at 30-minute intervals to Smart DCC (Data Communications Company), which provides the communication and data link between smart meters and energy suppliers, network operators and other authorised users.

DCC-channelled data has potential for supporting health and care services since it can reveal patterns of energy use over time as well as inactivity (discussed later). Whether load disaggregation approaches can be applied to 30-minute or even hourly data across 'unseen' households is the subject of ongoing research. For example, scientists at the University Strathclyde, Glasgow, have been able to disaggregate a wide range of home appliances from hourly data – even when unlabelled loads were contributing to meter readings (Zhao et al., 2020). The method did however require input of appliance wattage information beforehand. Next steps include investigation of more scalable or transferable approaches that can work on any unseen dataset.

Remote monitoring of appliance use in the UK (with consumer consent) will otherwise require one of two different data acquisition technologies: the CAD or current clamp. Unlike 30- or 60-minute disaggregation approaches, both methods could provide close to real-time monitoring capability.

Consumer access device (CAD) – 10 second data

The CAD is a secure device that can provide the consumer with tariff information and almost real-time data from the smart meter on energy consumption. Taking readings at 10-second intervals, the CAD can transmit data either inside the property (operating ZigBee and other communications protocols), or to an

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external internet location. In this way, the CAD could be used by NILM systems as a gateway, linking to Wi-Fi or 3G or 4G cellular, for example.

NILM research has shown how 10-second data can be used to detect high-energy appliances, such as a toaster, kettle, microwave, washing machine and electric oven (Chalmers et al., 2019). In this way, the CAD could enable inference of important activities such as eating, drinking and clothes washing. Ten-second data is not high-resolution enough to capture the use of low-energy devices, such as smartphone charging, televisions or computers.

CADs are not particularly expensive (starting at around £40) and are already installed by some energy providers. CAD-facilitated NILM systems in remote health and social care monitoring are therefore considered potentially scalable.

Current clamp – one-second or sub-second sampling

Current clamps are energy monitoring devices capable of capturing high frequency data, sampling at up to 1MHz (one million samples per second). This means they are able to detect both high-energy and low-energy devices. The capture of low-energy devices could be important to a healthcare monitoring system where such use forms part of the occupant's daily routine – for example, watching favourite TV programmes.

Providers of home energy-management services (HEMS) using NILM – including Smappee Infinity (Belgium), Sense and Powerley (USA), and Fludia (France) – are already offering this or similar technology to give consumers detailed information on a range of electrical devices used in the home.

For the purposes of future health and care monitoring, cost considerations are not so much linked to the clamp or sensor itself, more to the installation process (if requiring a technician), fast internet connection for data upload, and significantly higher data storage requirements. Home energy management services start at around $300 in the US and Canada,[7] and this is without the additional capabilities of behaviour/ADL mapping and monitoring. Full costs will need to be measured against the benefits derived from higher sampling rates, which could include greater accuracy of health monitoring systems.

7. For example, see SENSE (US/Canada): https://sense.com/product [priced $299, 28 September, 2020]

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Future SMETS technology

During our project period some experts pointed to a future opportunity to upgrade smart meters to enable one-second data sampling, as already available in Japan and some other locations. Providing greater data granularity, this faster sampling rate would enable a wider array of devices, including televisions and computers, to be recognised through NILM, without need for current clamp or sensor installation.

3.1.6 Synergies with the energy sector

We have seen how NILM R&D is variously focused on consumer savings, energy efficiencies and health and wellbeing monitoring. This raises the question as to whether synergies can be realised across sectors.

The CAD could be an important consideration for energy and health/care sector synergies. According to the UK trade association BEAMA,[8] CADs have already shown significant evidence of increased energy engagement in homes (without any NILM disaggregation service), in comparison to the more basic in-home-display (IHD) units (BEAMA, 2018).

If CADs become standard in our homes, the physical infrastructure would be complete for CAD-based (10-second) NILM services in health and care. In theory, the entire offering could be activated and delivered remotely, without any in-person visit to the monitored property. But with the business case yet to be made for CAD-facilitated health or care monitoring, any CAD roll-out needs to be driven by targets set for the energy sector and reduced carbon emissions.

Linked to this consideration is the energy sector's existing responsibility to identify customers' potential vulnerability. According to the energy regulator Ofgem, people in the vulnerable category include those of pensionable age and anyone living with young children or a disability, struggling financially or temporarily being less able due to an accident (Ofgem, 2019). Suppliers and network operators are expected to offer Priority Services Register (PSR) services covering a wide range of needs, not all of them financial. In the future, services could be extended to determine an offer of a particular remote care solution, which could be enabled by the energy supplier through the installation of a CAD, ideally at the same time as a smart meter installation.

8. British Electrotechnical and Allied Manufacturers Association (BEAMA) is the UK trade association for manufacturers and providers of energy infrastructure technologies and systems.

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Currently, CADs are not common to commercially available home energy management services that use NILM. Indeed, all of the services we reviewed during our research were using some form of clamp to allow measurement of sub-second data. These systems could certainly provide the starting point for (yet more complex) health and care monitoring systems, but costs would likely be significantly greater, as noted in the previous section.

The work of Informetis, referred to earlier, is interesting in this respect, because as a single commercial B2B entity specialising in NILM, it has formed partnerships to provide both energy management services and remote care monitoring in Japan. (These services are being kept separate at this present time.) Its assisted living application is exclusively sold by TEPCO energy partners for the Japanese market (Informetis, 2019).

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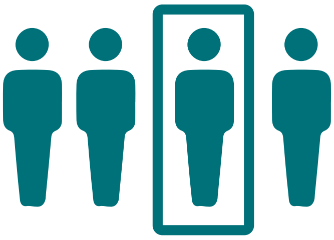

3.2 Population-level screening

3.2.1 Introduction

Population screening is the process of identifying people who may have an increased chance of a condition or disease. The screening provider then offers information to at-risk individuals, together with further tests and treatment where necessary, to reduce associated problems or complications. As stated by the UK government, 'screening should always be a personal choice' (PHE, 2013). Therefore, any use of smart meter data for this purpose would require direct consumer consent.

Our project highlighted two main ways in which smart energy data (both electricity and gas) may be used to support screening and monitoring at the population level:

1. Mapping of energy consumption over time to recognise daily and weekly energy habits of elderly people who live alone, or people who are in other ways potentially vulnerable. From anomalous energy use behaviour (deviation from routines), systems may be able to infer health or wellbeing risk.

2. Analysis of energy consumption, household data and weather data to identify fuel-poor and at-risk households during winter months. Priority households including frail elderly, people with learning disabilities who live alone, and families with newborns and young children.

In both cases, data resolution may not need to be any higher than that transmitted on a half hourly basis to the DCC. This is an important technical point, because DCC-enabled solutions should be inherently scalable. We explore each of these opportunities below.

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3.2.2 Recognising health risks from energy consumption patterns over time

We have already seen how research into the monitoring of behavioural routines through smart meter data often takes NILM as the starting point.

Behavioural routines might however be inferable simply from the use of energy over time. Researchers from Blekinge Institute of Technology, in Sweden, have reported a method to detect deviation from daily routines from energy consumption data alone, without the intermediate step of appliance disaggregation (Nordahl et al., 2019a & 2019b). In other words, the proposal is to build a model for daily routine directly from the time-based energy consumption data, rather than by the use of different appliances.

Data is processed from one-hour sampling intervals, a frequency considerably lower than that offered by smart meters. In research papers published to date, preliminary results appear promising, in that it seems to be possible to identify different energy consumption patterns as well as deviations from them: for example, increased energy consumption during the evening; lack of energy consumption during the morning; and nightly use of electricity (Nordahl et al., 2017).

The researchers' long-term aim is to use the approach for building an electricity consumption model that can be used for detecting abnormal behaviour of elderly individuals, such as those with early stages of dementia or other neurodegenerative diseases. (See also Sections 3.2.5 SERL (ii) and 4.4.)

It may be noted that Nordahl et al. have chosen to focus on electricity consumption patterns specifically, but their approach could be adapted to incorporate gas meter data. This would be possible in the UK using energy data obtained via Smart DCC. Use of this approach can be envisaged both within AAL monitoring systems and also population-level screening/monitoring, potentially managed by local government, third sector organisations or even utility companies.

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3.2.3 Detecting cold homes and health risks

Around 25,000 excess winter deaths occurred in England, Wales and Scotland in the 2018/19 winter, with leading causes being respiratory diseases (such as pneumonia), circulatory diseases, and dementia and Alzheimer's disease (ONS, 2019c; NRS, 2019).

Not in all cases may this link to fuel poverty or thermally inefficient homes: cold living conditions can also be due to 'perceived' fuel poverty (a perception that heating is unaffordable), self-neglect and/or a stronger desire to put savings and income towards other things.

In 2012, research from Age UK found that cold homes were costing the NHS in England £1.36 billion every year in hospital and primary care due to their devastating impact on older people's health.

Age UK: 'Still Cold' report, 2015

It is also important to recognise the extent of risk outside of social housing. Research from Scotland suggests that within low-income households, the proportion experiencing fuel poverty is in fact much greater for owner occupiers and private renters than it is for those in social housing: more than half compared to a fifth (Poverty.org).

Fuel poverty and cold living conditions can worsen many common physical and mental health problems for people of any age. In the case of children, risks to respiratory health, weight and susceptibility to illness are all increased (PHE, 2014).

Since energy data can very easily reveal patterns and levels of energy consumption over time, it could be used to recognise populations at risk of illness – and death – linked to cold living conditions. Certainly, the potential use of smart energy data for 'thermal safeguarding' is well recognised, with systems proposed to warn people (or their carers) when their home is unhealthily cold and/or damp (CSESF, 2018).

To recognise such risks accurately, the energy efficiency of the property needs to be known, since a well-insulated house requires less energy to maintain suitable living conditions than a poorly insulated one.[9] If the property has an up to date Energy Performance Certificate (EPC), this could be used in conjunction with

9. It should be noted that in addition to thermal efficiency, indoor air quality (and ventilation) is an important health consideration in terms of respiratory risks, e.g. exposure to radon, particulates and mould. See Hamilton et al., 2015.

3. Health and wellbeing monitoring using smart energy data

energy (gas and electricity) and local weather data to identify living conditions with possible health risks. But in many cases, an EPC may not be available or even still applicable – for example, where deterioration or unrepaired damage is impacting a building's thermal efficiency.

To assess the thermal efficiency of a given property, the whole-house heat transfer coefficient (HTC) needs to be understood. There is evidence from research that daily average electricity and gas readings, together with external air temperature and solar irradiance data, may be enough to enable an assessment of the HTC (Chambers, 2017).

Children living in cold, damp and mouldy homes have been found to be between 1.5 and 3 times more likely to develop symptoms of asthma than children living in warm and dry homes. Estimates from 2009 suggest that 1.1m children in the UK were affected by asthma – which can develop into a long-term and/or permanent condition (Public Health England, 2014).

The estimated cost associated with asthma to the NHS is at least £1.1 billion per annum

Mukherjee et al., 2016

It is an intriguing prospect, that if a system can non-intrusively estimate a property's thermal efficiency (e.g. supported with data obtained through Smart DCC), the same system may also be able to detect cold living conditions,

potentially linked to fuel poverty or neglect. While detection of a building's HTC is in theory a one-off assessment (based on historic data), the monitoring of health-related living conditions and thermal comfort would need to be ongoing to be of real value (see also Section 3.2.5, below: 'SERL').

The health and wellbeing utility of this technology could be enhanced by in-home smart temperature and humidity sensors, which would enable insights on risks of damp and mould (BSECC, 2015). Such data could, for example, be used to help combat risks of asthma, which are strongly linked to prolonged exposure to high levels of indoor dampness (PHE, 2014).

Another population-level screening opportunity could be realised with metadata from the smart metering system and other data directly held by Smart DCC. Data could be provided at an aggregated level (without consumer consent), retaining data privacy while still offering valuable insights to local authorities on

3. Health and wellbeing monitoring using smart energy data

which streets and districts may be struggling to meet need. Examples of metadata include patterns of pre-payment meter top-ups, low credit thresholds and emergency credit activation. Consensual use of metadata would allow insight of need at the household level.

3.2.4 Data acquisition and communications for population screening and monitoring

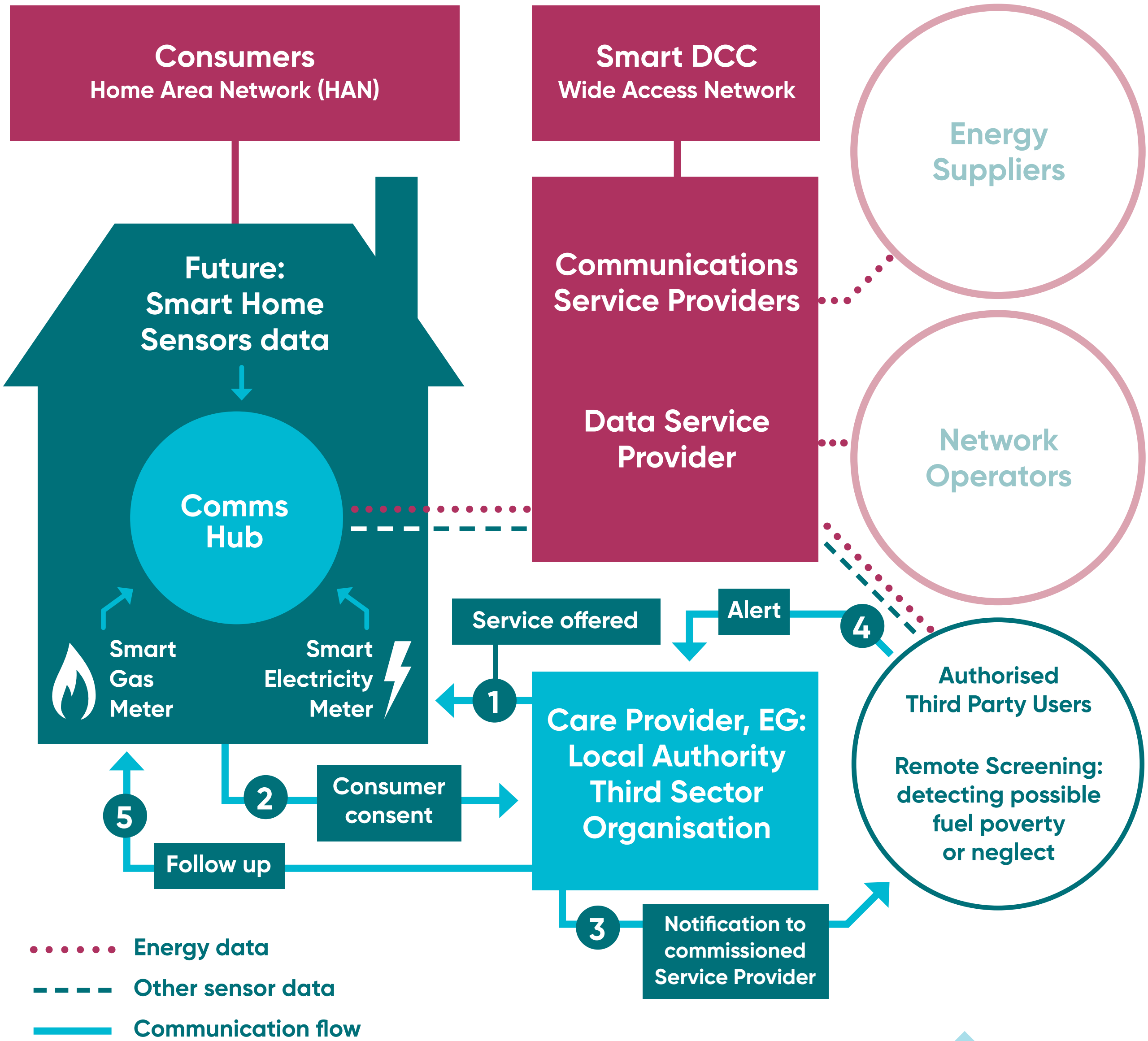
In theory, population-level screening and monitoring approaches described above could be achieved with electricity and gas data channelled by Smart DCC. Smart DCC offers nationwide connectivity, with 99% coverage, and seeks to support 'industry and customers through the development of new services, functionality and market-wide reform' (Smart DCC).

An authorised Smart DCC user (organisation), with customer consent, can access not only ongoing 30-minute aggregated data, but also a household's historical energy data (stored on the meter for a 13-month period), and other potentially relevant meta-data held by the DCC.

Assuming a fit-for-purpose system, Figure 3 shows a possible configuration for a commissioned screening/monitoring service by a local authority or third sector organisation. This service could potentially combine thermal efficiency testing and ongoing health and wellbeing services for consenting households.

3. Health and wellbeing monitoring using smart energy data

Figure 3: Possible configuration for population screening and monitoring using services of Smart DCC



The diagram suggests the future possibility of leveraging DCC communications technology to acquire smart home sensor (and IoT appliance) data alongside energy data. For example, with temperature and humidity data, third-party services could gain valuable insights on both cold and damp living conditions, with automated detection prompting alerts on health risks. Alerts could be followed up by the commissioning party, perhaps initially with a text or email with advice or signposting to free government insulation grants, or an offer of a visit to the property for a health and safety inspection.

3. Health and wellbeing monitoring using smart energy data

3.2.5 Research synergies

BEIS 'SMETER' innovation

The Department for Business, Energy and Industrial Strategy (BEIS) launched the Smart Meter Enabled Thermal Efficiency Ratings (SMETER) Innovation Competition in 2018. Now in its second phase, the competition is being driven by the government's Clean Growth Strategy, which aims to grow the economy while reducing greenhouse gas emissions in the UK. Of the total UK emissions, 13% comes from energy consumed in our homes.

The SMETER competition is providing companies with an opportunity to develop new technologies using household-specific consumption data from smart meters, combined with other data, for assessing the thermal performance of homes. Companies are able to acquire data either through the Smart DCC or a CAD. Either data acquisition method is thus considered scalable.

BEIS sees a variety of potential benefits resulting from a SMETER solution, including more accurate and reliable energy efficiency ratings and cost savings to the consumer. In terms of the overarching driver for the programme, the Clean Growth Strategy, SMETER is intended to enable fast and efficient recognition of houses in need of fabric efficiency measures (BEIS, 2019c). The government wants to see social housing and 'as many homes as possible' in the private rented sector upgraded to at least EPC Band C by 2030 (BEIS, 2019f, 2020c). The programme could therefore have significant impact on reducing fuel poverty.

BEIS has otherwise not highlighted any health and wellbeing application of SMETER technology – perhaps because a SMETER solution is not intended for the continuous monitoring of the same property. However, SMETER approaches may well have capacity to provide continuous remote monitoring of health and wellbeing risks linked to cold homes (see Smart Energy Research Lab (SERL), Section iii, below).

SMETER field trials are being hosted by Halton Housing,[10] an association at the forefront of investigating smart meter data potential in England (see also Section 3.1.3). The programme is due to finish in January 2021. If several solutions are

10. Halton Housing, in Cheshire, is providing 45 homes to take part in the SMETER trial. See article: https://www.haltonhousing.org/2019/09/halton-helping-to-transform-how-thermal-performance-of-homes-is-measured/ [Accessed 10.02/2020]

3. Health and wellbeing monitoring using smart energy data

considered viable, BEIS should bear in mind the additional health and wellbeing benefits SMETER innovation might bring when recommending solutions to achieve energy policy targets.

Smart Energy Research Lab (SERL)

The SERL is a five year project (2017–2022) aiming to provide a secure, consistent and trusted channel for researchers to access high-resolution energy data.[11] SERL's vision is to deliver a world-leading multi-disciplinary research programme, facilitated by a smart meter data portal. The portal will transform GB energy research through the long-term provision of high-quality, high-resolution energy data that will support the development of a reliable evidence base for intervention, observational and longitudinal studies across the socio-technical spectrum (Webborn, 2019). The SERL expects to have completed the recruitment of 10,000 GB households to its Observatory Panel in early 2021. SERL Observatory households have provided informed consent to collect their smart meter data, link it to relevant contextual data (e.g. survey, weather and EPC data) and provide it to accredited researchers via a secure lab environment.

Although public health is not the primary focus of the SERL research programme, there are several existing projects (and many potential future projects) that contain a significant health or wellbeing element which should be captured. Four of these projects are described below.

(i) Identifying wintertime comfort in UK homes

In winter, dwellings experience a time lag between turning on their central heating system and reaching their desired internal set point temperature. This project will attempt to characterise building thermal response and quantify the amount of time it takes for dwellings to heat up to the desired internal set point temperature during winter, and thus the amount of time in which they spend in thermal discomfort. This project is important for a number of policy-related reasons. For instance, when considering fuel poverty and cold related illnesses in homes; when considering the impact of extreme weather events and future climate scenarios on the housing stock; determining the potential impact on thermal comfort of switching to low-temperature heat emitters and technologies such as an air source heat pump, as part of a wider decarbonisation strategy; targeting homes for domestic retrofits; and evaluating the impact of energy efficiency policy on wintertime comfort.

11. SERL runs until August 2022. For more information, see https://serl.ac.uk/about-serl/

3. Health and wellbeing monitoring using smart energy data

(ii) Understanding habitual energy consumption

Research to date has analysed the shape of daily (24-hour) energy demand profiles, but very little if any research has analysed habitual electricity demand over periods of weeks or months. It is likely that seven-day cycles of demand exist due to repeating household practices (Mondays are like Mondays) but with seasonal variation and interruptions (e.g. holidays). However, we do not know the extent to which these daily or even half-hourly repetitive cycles exist, nor which kinds of households may exhibit different degrees of repetitiveness and whether there are regional variations. This project will use SERL Observatory data to analyse habitual patterns of household electricity demand to address this knowledge gap. There are clear synergies between this project and the work of the Blekinge Institute of Technology covered in Section 3.2.2 above.

(iii) Understanding domestic building thermal efficiency with smart meter data

The traditional method of estimating the energy efficiency of a building entails a physical survey undertaken by an assessor and the production of an Energy Performance Certificate (EPC), with a traffic-light system rating of A – G (most to least efficient). EPCs as a whole represent a time-intensive undertaking; they may also be carried out infrequently and too often show signs of unreliability (EUA, 2017; BBP, 2018). Building on the concept of the Heat Transfer Coefficient (see Section 3.2.3) or Power Temperature Gradient, this project will utilise half-hourly electricity and gas data, linked with weather and contextual information about the household and dwelling (which SERL collects through a participant survey) to open up new methods for evaluating the energy efficiency of GB homes, which could lead to the creation of 'smart EPCs'. It may also be possible to identify households of concern, such as those in fuel poverty or whose energy consumption is unexpectedly high for their dwelling efficiency, which could be useful for targeting valuable support, advice or initiatives to improve health and wellbeing outcomes in GB households.

(iv) The short- and long-term impact of COVID-19 on building energy demand and future decarbonisation

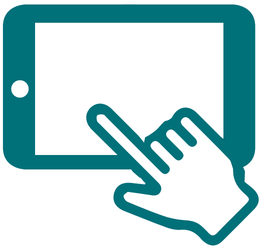
The coronavirus outbreak has seen the rapid reorganisation of society and substantial changes in energy use, with millions of workers at home and many offices and school buildings closed. As social distancing restrictions change according to the possible ebb and flow of the coronavirus, 'new normals' of energy demand are likely to emerge. By analysing the change in energy demand

3. Health and wellbeing monitoring using smart energy data

linked to survey data collected during lockdown, SERL is uniquely placed to contribute to important research on how the UK's energy needs have changed and may change in future as a result of the coronavirus pandemic. This includes analysis of how short- and long-term changes to energy consumption, patterns and behaviours might impact households in fuel poverty, for example, or other socio-demographic groups that may have been particularly impacted by lockdown restrictions.

Smart Energy Research Lab Observatory data is now available to accredited researchers via the UK Data Service secure lab (Study Number 8666). More information for researchers on how to access SERL data for research purposes is available here.

3. Health and wellbeing monitoring using smart energy data



3.3 Self-monitoring for wellbeing and home safety

Self-monitoring lies at the heart of smart home energy management systems (HEMS). These smart systems typically communicate through smartphone apps and are designed to increase energy awareness and control. In this way, consumers can take steps to reduce costs by reducing energy consumption and/or shifting energy use to more cost-effective times of the day, if time of use tariffs are in operation.

It has been suggested that using energy-aware systems to enable older people to improve their energy footprint can help reduce fuel poverty, which in turn improves their general wellbeing (Robinson et al., 2017). The communication of such information to the older consumer needs to be carefully considered: smartphone ownership amongst the over-75s is only around 20%, though the trend is rising rapidly (Ofcom, 2017). But energy-aware systems are of course not just applicable to older people and are currently being explored in the UK through the government's Smart Energy Savings (SENS) Competition (see next section).

As we have seen earlier, technology may have capacity to recognise cold homes simply from smart energy data and weather/contextual data – without any additional in-home hardware. This means that a service could provide prompts and information to opting-in energy consumers. This service could include practical advice and signposting to winter fuel help, such as the Warm Home Discount,[12] or to free government insulation grants. Such a service could be run by energy companies themselves.

Taking self-monitoring even further, some AAL solutions are directly aimed at the 'site owner', who receives health and wellbeing alerts in response to anomalous activity and deviations from their own routines (2020health 2020a, 2020c). Adapting this approach with smart meter data, it is possible to see NILM

12. The Warm Home Discount Scheme is available to those receiving the Guarantee Credit element of Pension Credit and to some low-income households that meet their energy supplier's criteria for the scheme.

3. Health and wellbeing monitoring using smart energy data

systems (see above discussion) likewise alerting the energy user of actions that may indicate a health risk or wellbeing concern. This could be a change of sleep patterns, detected by changes in the use of electrical appliances last thing at night, during the night and early morning. The self-monitoring system could then prompt the user to make a GP appointment to investigate a potential sleep disorder. In another scenario, a significant reduction in the use of a kettle could generate an alert to the user to make sure they are drinking enough to remain well hydrated. Integrating water consumption data from a smart water meter could deliver more precise prompts on hydration and personal hygiene.

Some HEMS aim to analyse appliance condition (and detect faults) through the use of energy submeters.[13] Anomalous appliance functioning may also be detected through energy disaggregation techniques. However, fault-detection methods using NILM have not yet matched the accuracy of methods using submetered data (Rashid et al., 2019). This may change with future iterations of NILM technology.

What NILM might do very effectively is detect appliances that have been left on, particularly ovens, which can run up costs and waste energy very quickly. Such continued forgetfulness could be recognised by the monitoring system, and if representing a change in behaviour, an alert generated to prompt follow-up with a clinician.

3.3.1 Scaling the technology

NILM-based HEMS are already commercially available in some countries but have little application to health and self-care. Most appear to use some form of current clamp or sensor to enable detection of both high- and low-powered devices, offering more control, scheduling capability and user information. There are clear opportunities to explore the capacity of the system to support self-care, but such data-heavy and relatively expensive approaches may have limited scalability in the near future.

A cheaper and more scalable option could be the CAD, with its lower sampling rates still sufficient to guide energy users towards safer and healthier routines. We should also bear in mind the potential of the smart meter alone: not just in terms of energy pattern monitoring, but also future capabilities of disaggregation technology to identify appliance use from low-resolution data.

13. For example, see Powerley: 'Appliance health monitoring'. https://www.powerley.com/platform/ [Accessed 18 February, 2020]

3. Health and wellbeing monitoring using smart energy data

3.3.2 Research synergies

The existence of home-energy management systems is reason enough to be looking at solutions not in energy and health silos, but in broad-use combinations.

Energy companies are well placed to be researching solutions across the domains of energy efficiencies and self-care, particularly since they can invite participation in schemes at the point of new contracts. They potentially have data insights to return not just energy consumption advice but also health and wellbeing alerts and even signposting, derived from information collected on the home and its occupants, energy usage and consumption patterns, and weather data.

With regard to government-sponsored research, synergies could be realised through the BEIS Smart Energy Savings (SENS) Competition, launched in February 2019. The aim of SENS is to encourage the development and trialling of innovative products and services to deliver additional energy savings in homes through the use of smart meter data (BEIS, 2019d).

In its guidance notes, BEIS asked bidders to consider additional benefits, including ‘improved consumer wellbeing, including health, comfort, household harmony and sense of control over energy use, bills and indoor environment’ (BEIS, 2019e). With competition partners now selected, it is clear that some hope their solution will contribute to fuel poverty reduction through consumer cost savings. Whether participants are seeking to improve consumer health in other ways is unclear (BEIS, 2019d).

4. Smart energy data in combination with other AAL technologies

4.1 Introduction

Smart energy data could combine in multiple ways with environmental data and ambient assisted living (AAL) technologies for the purposes of remote monitoring. So far, little research has been undertaken.

System configurations using home temperature and humidity sensors in combination with smart energy data have been described, but not yet tested. These could be extended with water consumption data from smart water meters, which have potential to provide yet deeper insights into health-related behaviours, particularly in terms of hydration and hygiene (Fell et al., 2017). Uses for a combinatorial electricity-gas-water monitoring approach can be envisaged both at the individual and population level. The inclusion of water data could for example help identify families struggling with 'hygiene poverty'.

The lack of research activity into combinatorial AAL approaches incorporating NILM may seem surprising, given the popularity of smart plugs and sockets in current AAL solutions. At the same time, system complexities and the difficulties of undertaking clinical trials are no doubt presenting substantial challenges to progress. We must also remember that NILM remains an active area of research in its own right, especially in the refinement of energy disaggregation (see Section 3.1.2).

In this section, we present two case studies from recently completed projects that highlight both challenges and opportunities in smart energy data fusion with other AAL technologies.

4. Smart energy data in combination with other AAL technologies

Case Study: City4Age project

Extending from smart home to smart city, the recent multi-site City4Age project[14] had particular focus on monitoring frailty and cognitive decline in older adults. Test bed sites were located in Athens, Birmingham, Lecce, Madrid, Montpellier and Singapore, where solutions were explored in different use case scenarios, covering indoors (at home or within a senior centre) and outdoors (within the city). In-home technologies included discreet motion, contact and bed sensors, while outdoor monitoring used a smartwatch or smartphone locator app in conjunction with beacons deployed in the participants' places of interest (e.g. bus and metro stations, cinemas, restaurants). During the project, data was analysed using machine-learning processes to enable the detection and prediction of changes in frailty and mild cognitive impairment among participants.

One of the proposed solutions to emerge from the City4Age project was a hybrid approach to energy consumption monitoring. The system proposes a smart meter to continuously collect data on the global power consumption in the house, while smart-plugs detect the usage of devices with low power consumption. Global power consumption[15] is transmitted to a cloud-based server where appliance disaggregation can be applied to devices with a well-defined power signature (microwave oven, washing machine, fridge, etc.); meanwhile, Wi-Fi or Bluetooth Low Energy (BLE) enabled smart-plugs are used to monitor certain low-power-consuming devices, which would otherwise be very difficult to detect (especially when used at the same time as other appliances). This information is also sent to the cloud-base server for data fusion.

The solution was considered both unobtrusive and low cost, and could be combined with other monitoring solutions integrated in the City4Age platform to provide more accurate data to feed risk analysis algorithms related to MCI and frailty. Researchers reported that future work would deal with the refinement of the algorithm for appliance identification running on a Cloud Building Block.

Following the City4Age project – which demonstrated some evidence of cost-effectiveness (Mercalli et al., 2018) – GATEKEEPER was launched in October 2019 as a 3.5-year European Multi Centric Large Scale Pilot on Smart Living Environments. Running eight pilot sites across Europe, including one in Milton Keynes, the €22.6m programme is further exploring AAL solutions for personalised early detection and intervention. There is a stronger clinical focus in this project, including AAL solutions for COPD (exacerbations management), diabetes (predictive modelling of glycaemic status) and Parkinson's disease treatment decision support systems.[16]

Sources:
City4Age website https://www.city4ageproject.eu/, Almeida et al., 2019, Mercalli et al., 2018, Gatekeeper Project website https://www.gatekeeper-project.eu/

14. City4Age project was supported with €4.5m funding from the EU Horizon 2020 research and innovation programme. See: https://cordis.europa.eu/project/id/689731 [Accessed 27 Jan. 20]
15. Consumption is detected by a meter that counts the blinks of the central power meter's LED.
16. For more information see Gatekeeper website: https://www.gatekeeper-project.eu/GATEKEEPER and CORDIS: https://cordis.europa.eu/project/id/85722

4. Smart energy data in combination with other AAL technologies

Case Study: Technology Integrated Health Management (TIHM) for dementia

Launched in 2016 as one of the NHS Innovation Test Beds, TIHM was supported with £5.2 million in funding from the Department of Health, NHS England and the Office for Life Sciences. The study was led by Surrey and Borders Partnership NHS Foundation Trust (SABP), with principal collaborators including the Centre for Vision, Speech and Signal Processing at the University of Surrey and smart home monitoring provider Howz.[17]

A six-month trial involved 204 people with mild to moderate dementia and their live-in carers (also 204). A control group provided a benchmark against which to assess the effectiveness of the TIHM technology.

A network of digital devices was installed in homes, comprising sensors, monitors and a gateway device. The live-in carers recorded vital sign data such as blood pressure, body temperature, pulse, oxygen saturation, weight and hydration. Sensors monitored a person's movements in the home and environmental data, such as room temperature and light. Whole-house energy consumption was also measured, with disaggregation methods applied to recognise the use of specific kitchen appliances.

If the technology identified a health, environmental or technical problem, an alert was triggered and flagged and prioritised on a digital dashboard, monitored by clinicians. ADLs, as well as agitation and unusual patterns, were detected with a reported accuracy of 80%.

Of the 16,553 alerts analysed during the trial period, 60% were clinical, 26% were technical (related to the technology) and 14% environmental. Clinical alerts deriving from physiological measurements were most common. Complex algorithms developed towards the end of the study led to 1,769 alerts for agitation, irritability and aggression, and 124 alerts for urinary tract infection.

Evaluation findings (SABP, 2019):

- Participants with dementia experienced a statistically significant and sustained reduction in neuropsychiatric symptoms associated with dementia, including depression, agitation, anxiety and irritability.
- Of the people with dementia and their carers interviewed, 70% were overwhelmingly positive about the technology; a further 19% said they would recommend TIHM if the user-friendliness and reliability of some devices was improved.

The evaluation found no evidence of reduced hospital admissions.

A second six-month study followed in 2019, involving 120 people with dementia and their carers, with the aim of further refining the TIHM for dementia technology.

17. Other partners involved in TIHM included the Royal Holloway University of London, Alzheimer's Society and, in phase one, eight technology SMEs (including Howz).

4. Smart energy data in combination with other AAL technologies

An important consideration for the second pilot was the scalability of the monitoring technology, particularly in terms of tracking appliance use. Howz used energy disaggregation technology in TIHM phase 1 and had applied similar processes in a 2017 stroke study in Greater Manchester, involving 19 participants (Rogerson, Burr & Tyson, 2019). However in Phase 2 of TIHM, Howz opted for smart plugs for individual appliance monitoring, considering this approach more straightforward and scalable than NILM techniques at this current time. (Howz nevertheless remains active in smart energy data research: see Section 4.4 below.)

TIHM is now 'live' and has seen increased use during the COVID-19 pandemic among people with dementia and their carers who live in Surrey.[18]

Case study sources:
University of Surrey, 2019. Surrey and Borders Partnership NHS Foundation Trust: Final Evaluation Report. School of Health Sciences, University of Surrey, Surrey and Borders Partnership NHS Foundation Trust: TIHM web pages (www.sabp.nhs.uk/tihm), 2020health interviews with Howz, January/February 2020.

4.2 New paths

Some researchers have commented on the limitations of smart energy data as a stand-alone monitoring solution, arguing that even the most sophisticated methods so far explored, i.e. NILM, would benefit from other behaviour change detection methods in order to improve accuracy (e.g. Alcalá et al., 2017b).

While adding further monitoring technology to NILM could present challenges to scalability, a number of AAL providers offer relatively cheap smart solutions (e.g. smart plugs and movement sensors), which can be posted to households along with an associated gateway device.[19] This kind of 'plug-and-play' approach normally requires broadband, but otherwise may not require a technician's visit.

Another combinatorial approach may see AAL sensors used alongside data analysis of energy consumption patterns over time, as explored by Nordahl et al. (see Section 3.2.2), without integrating the more advanced processes of NILM. The health technology provider Howz is planning to test the utility of energy

18. For further information see: https://www.sabp.nhs.uk/TIHM/about
19. Examples include Howz and Kemuri.

4. Smart energy data in combination with other AAL technologies

pattern analysis in a forthcoming pilot, supported by NHSX and Surrey & Borders Partnership NHS FT, and in collaboration with East Midlands AHSN, a large GP practice and De Montfort University in Leicester. The goal is to offer the public a free monitoring service based on electricity consumption patterns only. Customers will be able to purchase an upgrade for additional equipment in the home, such as door and movement sensors, for closer real-time informal care monitoring (2020health, 2020d).

Other scalable solutions to complement smart energy data include smartphone apps, as explored in the City4Age project. Like smart meters, smartphones are set to become virtually ubiquitous, with ownership already at 80% for the 55–75 age group in 2019 (Deloitte, 2019). With AAL apps installed, smartphones can deliver alerts on detected falls (e.g. Ong et al., 2018, for Parkinson's sufferers) and enable outside monitoring (e.g. Grossman et al., 2018, for people with dementia). Such technology may not be relied on by itself, since the user may not always be carrying their phone or a Bluetooth device, but it could provide carers with important additional information beyond smart meter data in the monitoring of vulnerable older people.

Looking a little further ahead, MIT researchers are exploring innovative in-situ monitoring with Person Re-Identification (ReID) technology using wireless signals in the Wi-Fi frequency range. In the context of retirement homes and private dwellings, the radio frequency (RF) technology can recognise intrinsic features of the human body, such as body size or shape, even walking style, with RF signals able to traverse walls and operate in dark settings (Fan et al., 2020). While RF-ReID has some current limitations in multiple occupant settings,[20] it could add important health and wellbeing insights at low cost in single-occupant households when combined with smart energy data. These include faster recognition of falls, and deeper insights on health changes and wellbeing status linked to mobility and movement characteristics.

Caveat!
It is important to stress that in-person contact, assistance and interaction will always remain vital for the wellbeing of the monitored individual. AAL solutions should not be thought of as a replacement service, at least in contexts outside of COVID-19 lockdown. No doubt many more people are now aware of the deeply negative impacts of social isolation.

20. For example, RF-ReID may fail to recognise a person who carries something that changes their walking style.

5. Barriers to scaling health and care monitoring using smart meter data

During our project period we reviewed a range of potential barriers to progress in using smart meter data in health and care monitoring. This review process included discussions at our February (2020) workshop with expert stakeholders from a wide range of backgrounds, sectors and disciplines.

Barriers to progress discussed below can be broadly compartmentalised into three areas: research challenges (5.1); technological and communication challenges (5.2); and public-facing issues, including regulation (5.3–5.5).

5.1 Research challenges: proposition and collaboration

In-depth research into smart meter data in health and care contexts is reliant on multi-disciplinary collaboration, spanning computer science, engineering, energy and healthcare. If such collaboration is not achieved, studies remain only theoretical, with little evidence of real-world scalability and clinical validity.

The proposition of monitoring ADLs through appliance use is only about 12 years old. And while NILM research in contexts of health and care has used 'real-world' datasets, the vast majority of research teams involved have been based in computer-science and engineering departments.[21] Examples of truly multi-disciplinary collaborative research are rare, and very few studies using energy data have involved recruited participants.

The multi-disciplinary needs of real-world research are no doubt a challenge to testing such systems, and yet other AAL research projects using machine learning systems appear to have traction. These include the SPHERE project in Bristol and the EU Gatekeeper project. Both are running multiple pilots and employing a variety of sensors and machine-learning processes for remote monitoring, whether exclusively in the home or extending out to smart city. These projects are also exploring a range of clinical-monitoring uses of the technology, including

21. For example, Blekinge Institute of Technology, Sweden; Electronics Department, University of Alcalá; School of Informatics, Aristotle University of Thessaloniki, Greece.

5. Barriers to scaling health and care monitoring using smart meter data

Alzheimer's, post-op recovery and reablement, Parkinson's, diabetes (predictive modelling of glycaemic status) and COPD exacerbations management.[22]

Health-oriented studies involving smart energy data have had particular interest in dementia, even though monitoring applications could extend to a wide range of disabilities (progressive or otherwise). Opportunities to broaden the research focus need to be recognised by a range of academic institutions and supported by funding bodies.

Social care testing of the technologies is likely to advance more quickly – driven by commercial R&D – with services privately purchased or officially piloted by public health bodies. This is starting to be seen in other AAL monitoring solutions involving machine-learning, particularly where deployed technology does not need classification as a medical device (with no clinical decision-making derived from it). Interest in smart energy data solutions may be significant given the increasing demand for care and decreasing service capacity to deliver it (NHS Providers, 2018).

5.2 Technological and connectivity limitations

We have noted earlier the present limitations of NILM. Reliable recognition of electrical devices and appliances in the home remains an active area of research in computer science and machine learning. Other challenges include the ability to detect low-wattage consumer electronics where multiple devices are used at the same time.

Researchers at Liverpool John Moores University have attempted to jump some of these hurdles by focusing only on high-energy devices that give indication of ADLs and important behavioural routines. They have also been able to cluster particular types of appliance, since the electrical signatures of different makes

22. More information can be found on project websites: Sphere https://www.irc-sphere.ac.uk/research [Accessed 20.1.20.]; Gatekeeper Project: https://www.gatekeeper-project.eu/GATEKEEPER [Accessed 20.1.20.]

5. Barriers to scaling health and care monitoring using smart meter data

of kettle, toaster or oven are very close to each other. But their system has yet to be tested across a large range of houses, with unseen environments, and there remain challenges in the recognition of appliances that are turned on in quick succession (2020health, 2019).

In terms of infrastructure and connectivity, smart meters remain the lesser-used metering technology in homes across the UK, despite their rapid deployment. Moreover, SMETS1 meters, installed during the first phase of the roll-out scheme, have sometimes reverted to 'dumb mode' as the consumer switches energy supplier. These issues do not present major barriers to progress, however. Smart meters are set to be virtually ubiquitous within a few years, and Smart DCC is solving interoperability problems with the first-generation smart meters by having them enrolled onto their secure network.

Other communications challenges need to be solved in cellular and Wi-Fi connectivity. These could impact the usability of a CAD, which typically relies on either a Wi-Fi or cellular connection to upload information to the Internet. In some rural parts of the country, cellular connection is either intermittent or non-existent. Furthermore, households with one adult aged 65 years and over have the lowest proportion of Internet access – just 59% in 2018 (ONS, 2018b). Such households are the target demographic of many AAL solutions.

The good news for AAL providers is that the 65+ single-occupant households have seen strong growth in internet access in recent years, up 23 percentage points between 2012 and 2018. In overall connectivity, the UK was ranked fifth within the EU in 2018. The UK is therefore well positioned to be researching smart energy data in health and care monitoring, and testing this at scale, as and when technologies demonstrate validity.

5. Barriers to scaling health and care monitoring using smart meter data

5.3 Privacy and regulation

Living in the digital age has brought increased awareness of data privacy. Striking the right balance between using personal data for commercial or welfare purposes and protecting and upholding the individual's right to data privacy is a challenge. No less so in the case of smart energy monitoring.

Substantial safeguards are in place to ensure that sensitive data are not accessible by anyone other than the individual concerned.[23] As service capabilities evolve, an ongoing process of reassurance is likely to be required to allay users' fears and concerns and ensure appropriate regulatory oversight keeps in step with developments in the field.

Third-party services certification with the National Cyber Security Centre's Cyber Essentials Scheme could be a consideration in this regard, helping to demonstrate to consumers that cyber security measures are in place and taken seriously. The Information Commissioner's Office (ICO), which has responsibility for upholding General Data Protection Regulation (GDPR) in the UK, has recommended Cyber Essentials as a good starting point for the cyber security of all IT necessary to hold and process data.[24]

Research by the Public Interest Advisory Group (PIAG) on access to smart meter data for a public-interest purpose, indicates that consumers find it a challenge to determine the risk and benefits involved with the use of their data, but on the whole consider smart meter data to be less sensitive than other forms of data. It appears consumers generally expect the regulator to take measures to protect their interests (Frerk et al., 2019).

Once smart energy data becomes 'health and care data', information from the smart meter will undoubtedly be considered much more sensitive. This will be

23. For example, see Smart Energy Code. https://smartenergycodecompany.co.uk/the-digital-smart-energy-code/ [Accessed 12th March 2020]
24. For more information, see Information Commissioner's Office: Security. https://ico.org.uk/for-organisations/guide-to-data-protection/guide-to-the-general-data-protection-regulation-gdpr/security/ [Accessed 12th March 2020]

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particularly relevant as AI continues to learn more about who each person is as an individual. The public may fear data breaches or that information obtained may be used against them, for example by insurance companies or credit lenders.

From a services point of view, there are important considerations for consumers who routinely switch energy provider, since it is possible to see energy providers actively involved in supporting care monitoring (as in the case of TEPCO[25] in Japan). Customers would need to be confident of both data privacy and continuity of care-monitoring services when switching. The bundling of services could itself have a chilling effect on switching, so clear regulatory guidelines would be required.

The Austrian firm Solgenium has been running a parallel study to their SOLARIHS pilot (Section 3.1.3 above) with multi-disciplinary oversight to examine the privacy consequences of its research. Access by Solgenium to smart meter data is from anonymised secure data storage, with only the clinician and patient being able to link the analysis with other data in the patient's healthcare record. Patients can access the audit trail to their health record (to check who has seen what) and also have the ability to revoke access by others.

Source: 2020health interview, 23 September, 2020.

Thought needs to be given also to behaviour and ADL data, and how this might be transferred across providers to ensure no interruption to services. Such issues will be important in clinical contexts (perhaps less so in contexts of informal care) and will require relevant data protection legislation and codes of practice.

Where monitored individuals move out of tele-monitored properties, privacy assurances will be needed for new occupants who do not want the smart meter or consumer access device (CAD) left 'live' or 'open' to the monitoring of their energy patterns. Indeed, they may well have no knowledge of a previously installed service, and their own data could be exposed to a person or third party who had monitored the former occupant. Energy companies should therefore be notified by third-party tele-monitoring services who arrange to obtain energy data from the smart meter, CAD or current clamp, so as to ensure oversight and data privacy at the point of new contracts with new occupants.[26]

25. TEPCO: Tokyo Electric Power Company
26. This is to propose a tightening of regulation around third party arrangements described by Ofgem in 'Extending the smart meter framework for data access and privacy to Remote Access Meters' (2014).

5. Barriers to scaling health and care monitoring using smart meter data

As new technologies evolve and develop, so does the need for effective and 'connected' regulation, and this requires consideration of the policy environment in which regulatory instruments operate (Raab, 2008). Regulation needs to offer enough protection to manage the risks involved and provide cover for current work, while at the same time not stifling innovation and potential social and economic benefits that could be realised through future advances.

5.4 Consent

Negative press surrounding smart meters, with some widely publicised personal accounts of smart meter failures, may well have fomented resistance to the smart meter roll-out among some consumers, and perhaps continues to do so (e.g. Smith, 2019; Clark, 2020, Brignall, 2020). Moreover, whereas the public can choose online banking, credit cards and social media platforms, smart meters are in effect a state intervention, and personal information derived from them is only going to grow. Strategies to build and maintain public trust in sharing energy data will be critical as innovators probe possibilities in health and care domains. Smart meters may not be as data-sensitive as social media or online searches and purchases, but the public must be aware how data are to be used and how to opt-in and opt-out.

It is of course difficult for goverment to issue clear guidelines on emerging possibilities. In its Review of the Data Access and Privacy Framework (DAPF) (2018), BEIS acknowledged the possibility of smart meter data in 'supporting independent living and social care by monitoring activities and behaviours within the home'. However, the department concluded that at this current time:

'... limited evidence is available to assess the extent to which these opportunities are being realised and this is an area where further monitoring will be necessary to support ongoing evaluation...' (6.12)

5. Barriers to scaling health and care monitoring using smart meter data

The public is not without current protection, however. Supporting Ofgem's existing guidlelines is General Data Protection Regulation (GDPR), which came into force in May 2018. Telecare providers using energy data will need to be mindful of GDPR 'data subject' rights, which include: the right to be informed when personal data are being collected and processed; the right of access; and the right to object to certain processing activities (including profiling) and to automated decision-making (ICO n.d.).

The new right to data portability (GDPR 2018, Article 20), allowing individuals to obtain and reuse their personal data for their own purpose across different services and IT environments – in a manner which is safe, secure and does not affect its usability – also requires careful consideration. It raises the question as to what extent personal data fed into machine-learning systems (and behavioural insights derived therefrom) should be transferrable to other parties at the request of the monitored individual.

Guarantees will of course be needed to ensure data acquired by third parties for health and care insights are not then used by the same firm (or its affiliates) for the targeting of other services, without clear, opting-in consent. With health-related data, there is indeed the risk of exploitation, should users of such services be in a particularly vulnerable state.

Vulnerability and consent also arise in the issue of 'deprivation of liberty'. In new legislation last year (Mental Capacity (Amendment) Act 2019), Deprivation of Liberty Safeguards (DoLS) were replaced by a new scheme called Liberty Protection Safeguards (LPS), which similarly aim to ensure that in cases where an individual lacks capacity to consent, care provided does not restrict that person's liberty and is both appropriate and in their best interests. Whereas DoLS only applied to hospitals and care homes, LPS extends to other contexts, such as supported living and private and domestic settings. LPS in AAL monitoring may include services offered to a person with a learning disability or a person whose mental capacity fluctuates. However, it is unlikely that LPS considerations for smart energy data monitoring would be meaningfully different to those for any other non-intrusive AAL monitoring system.[27]

27. In England and Wales, healthcare technology can be used in the home without consent if a 'best interest' decision is obtained, in accordance with the Mental Capacity Act (2005). Scotland's decision-making in this area is covered by the Adults with Incapacity (Scotland) Act 2000, and Northern Ireland's in the Mental Capacity Act 2016.

5. Barriers to scaling health and care monitoring using smart meter data

Despite many existing laws surrounding privacy, regulation and consent, it seems clear that ongoing evaluation by BEIS and Ofgem will be needed to ensure full data protection within an entirely new, and potentially imminent, telecare offering involving smart meter data.

5.5 Complexity of the service offering

In general, user and clinician experience of remote care monitoring has been reported as positive where the technology has been deployed in response to identified need, with appropriate privacy assurances and with clear realisation of benefits (Tsertsidis et al., 2019).

Researchers and service providers may have to draw comparisons with other AAL approaches to communicate the value of health and care monitoring using energy data. The technicalities of the propositions are complex, and consumers need a very clear understanding of 'what's in it for me?' to be amenable to buy-in and data sharing. People need to see and understand how the technology integrates into their lives and what benefits it will bring.

Discussing research progress in clinical contexts, one start-up we spoke to emphasised the importance of capturing the imagination of clinicians, who could then support study recruitment, explain the offering and assist clinical oversight of research programmes.

In many cases it will be the older population (who generally have less technology literacy) who stand to gain most from the benefits offered by smart meter data. The engagement of family members who find themselves taking on caring roles for aging parents is likely to be important.

During our project period, a housing association disclosed that in one recent AAL pilot, participation consent came principally from the monitored party, not jointly with family members, who were asked to receive monitoring alerts in the event of

5. Barriers to scaling health and care monitoring using smart meter data

a detected health risk or anomalous behaviour change. Pilot participants received poor support in some cases, because family members, as ‘named contacts’ (or ‘first responders’), struggled to grasp the point of the pilot study.

Some companies have reported face-to-face meetings to be far more effective than paper-based advertising in clarifying details, allying fears and aiding take-up of AAL monitoring solutions (2020health, 2020e). However, while face-to-face might be a plausible approach for personalised systems in health and care contexts, it is far from scalable for screening and long-term monitoring at the population level.

Public health bodies will need to undertake some careful and targeted marketing to understand how to communicate the benefits of screening and monitoring services through smart meters at the population level. They will need to work with stakeholders to allay fears of Big Brother surveillance and create simple messages to help at-risk households make sense of how smart meter technology can make a positive difference in their lives.

6. Conclusions

This review has explored current technological capability to use smart energy data in remote health and care monitoring, and perhaps in future assist clinical diagnosis and decision-making. However, real-world demonstration of how to capture and utilise smart energy data in such contexts remains very limited.

A lack of progress, particularly in clinical contexts, is perhaps in part due to the fact that government and institutional funding opportunities have not recognised the specific multi-disciplinary requirements for rigorous clinical research involving smart energy data and machine learning.

Research projects often end up being siloed in either energy or health domains. Government and UKRI might want to facilitate cross-sector innovation by creating research funding opportunities that explicitly link energy and health outcomes. Exploring opportunities to share data securely across existing research data portals such as the Smart Energy Research Lab (energy) and UK BioBank (health) would further facilitate cross-sectoral research.

Cross-sector innovation is needed to realise the full potential of SMETER – thus beyond its ambition to accurately measure the thermal efficiency of buildings. BEIS has not yet described opportunities to investigate simultaneous health and wellbeing benefits through the same technology. The department has opportunity to consider the wider societal applications of these technologies at the evaluation stage (end of 2020). We would encourage BEIS to consider how SMETER might scale as a screening and monitoring solution for the detection of possible fuel poverty and unhealthy living conditions.

Linked to this public health solution are opportunities to use metadata and other data held by the DCC, particularly on patterns of pre-payment meter top ups, low credit thresholds and emergency credit activation. Aggregated data could provide insights to local government on streets or districts struggling to meet need, thereby supporting targeted intervention.

Also important is exploration of how smart energy data may help relieve health and care system stresses. Systems using NILM, analysing health and wellbeing status at the single household level, offer potential to mobilise social capital and networks (as other AAL monitoring solutions are doing currently) by 'recruiting' family members and friends to respond to alerts prompted by unexplained changes in routine and ADLs. At the same time, these machine-learning systems

6. Conclusions

will need to be explored for the benefits they might bring to healthcare workforce productivity, especially for social care workers and community nurses.

The new ethical issues that arise from smart meter data in health contexts will need careful consideration. These include assurances that data acquired by third parties for health and care insights are not then used by the same firm (or its affiliates) for the targeting of other services, without clear, opting-in consent. The industry will almost certainly struggle to convince the public if the latter feel duped by fine-print or by multiple pages of 'terms of use' that few have time to read.

For the UK government, the smart meter roll-out is a key strategy in meeting its targets of reduced greenhouse gas emissions. But the government also needs to consider meeting other targets by utilising the same or very similar technology, thereby reducing excess winter mortality; addressing system pressures from an aging population; supporting family caring needs; and giving timely support for those with Alzheimer's, dementia, Parkinson's, MS and other disabling long term conditions.

Research suggests these vulnerabilities and conditions can all be supported by information derived from smart meter data. But without government and institutional research funding that recognises the specific multi-disciplinary collaboration required for robust clinical research involving smart meter data, we will still be confined to discussing important possibilities ten years from now.

Appendix A: Smart Future Healthcare workshop participants

Jon Paxman	Researcher, 2020health (SFH Project Lead)
Julia Manning	Founding Director, 2020health
Matt James	Assistant Director, 2020health
Dr Enrico Costanza	Associate, 2020health; UCL Interaction Centre
Dr Helen Meese	Managing Director, The Care Machine Ltd
Dr Michael Fell	Senior Research Fellow at Bartlett School Env, Energy & Resources (UCL)
Barney Smith	Founder/CEO, Perform Green
Dr Carl Chalmers	Senior Lecturer, Faculty of Engineering and Technology, Liverpool John Moores University
Dr Paul Fergus	Reader (Associate Professor) in Machine Learning, Department of Computer Science, at Liverpool John Moores University
Louise Rogerson	Co-founder and COO, Howz
Simon Elam	Principal Research Fellow at UCL Energy Institute, Director of the Smart Energy Research Lab
Jay Chinnadorai	Board Advisor: Informetis; founder of Sumtotal; former Vice President of Sony Europe
Matt James	Business Development Manager, Smart DCC
Frances Williamson	Head of Communications and Industry Engagement, Chameleon
Gav Roberts	Disruption Officer, Halton Housing
Dame Helena Shovelton	Trustee, Independent Age; former Chief Executive of the British Lung Foundation
Russ Charlesworth	Director of Health & Social Care, Socitm Advisory
Hannah Trent	Senior Strategy Manager – Smart; British Gas
George Walters	Head of New Business, Utilita
Carole Peylaire	Senior Manager of Residential Customer Development, Innovation department – EDF/Blue Lab
Dr Ruth Chambers	Staffordshire STP's Clinical Lead for Technology-enabled Care Services Programme, Digital Workstream
Chris Ward	Innovation Lead – Healthy Ageing – Innovate UK
Dr Adel Baluch	Medical Expert at Ada Health | Primary Care Doctor
Dov Boonin	SMETER lead, Science & Innovation for Climate & Energy, BEIS

Observers

Liz Harper	Policy and Public Affairs Manager, Smart Energy GB
Elaine Benzies	Policy and Public Affairs Officer, Smart Energy GB

Appendix B: Interviews and correspondence

Interviews

Prof Sarah Tyson	Professor of Rehabilitation in the Division of Nursing, Midwifery & Social Work. University of Manchester
Louise Rogerson	Founder and COO, Howz
Jonathan Burr	Founder and CEO, Howz
Dr Carl Chalmers	Senior Lecturer, Faculty of Engineering and Technology, Liverpool John Moores University
Dr Paul Fergus	Reader (Associate Professor) in Machine Learning, Department of Computer Science, Liverpool John Moores University
Matt James	Business Strategy Manager, Smart DCC
Lee Reevel	Innovation Lead – Halton Housing Lead Disruptor
Andreas Diensthuber	Founder, Solgenium, Austria
Ben Roberts	Research Associate (SMETER), Loughborough University
Gerry Hodgson	CEO, Cascade 3d

Correspondence

Dr Leonard Anderson	CEO Kemuri Ltd
Jay Chinnadorai	Informetis / SumTotal
Marco Carulli	Programme Operations Manager, EU AAL Project
Dr Larissa Nichols	Senior Research Fellow – ARC Linkage Digital Energy Futures Project, Monash University (Australia)
Gav Roberts	Halton Housing
Frances Williamson	Head of Communications and Industry Engagement Chameleon Technology

Appendix C: Steering Group

Dan Byles	CCO UnifAI Technology
Simon Elam	Principal Research Fellow at UCL Energy Institute, Director of the Smart Energy Research Lab
Dr Michael Fell	Senior Research Fellow at Bartlett School Env, Energy & Resources (UCL)
Dr Helen Meese	Founder & CEO, The Care Machine Ltd
Barney Smith	Founder and CEO Perform Green
Angela Thompson MBE	Retired NHS Director

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