Persuasive digital health technologies for lifestyle behaviour change

Doctoral Thesis

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By

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Abstract

Background: Unhealthy lifestyle behaviours such as physical inactivity are global risk factors for chronic disease. Despite this, a substantial proportion of the UK population fail to achieve the recommended levels of physical activity. This may partly be because the health messages presently disseminated are not sufficiently potent to evoke behaviour change. There has been an exponential growth in the availability of digital health technologies within the consumer marketplace. This influx of technology has allowed people to self-monitor a plethora of health indices, such as their physical activity, in real-time. However, changing movement behaviours is difficult and often predicated on the assumption that individuals are willing to change their lifestyles *today* to reduce the risk of developing disease *years or even decades later*. One approach that may help overcome this challenge is to present physiological feedback in parallel with physical activity feedback. In combination, this approach may help people to observe the acute health benefits of being more physically active and subsequently translate that insight into a more physically active lifestyle.

Aims: Study One aimed to review existing studies employing fMRI to examine neurological responses to health messages pertaining to physical activity, sedentary behaviour, smoking, diet and alcohol consumption to assess the capacity for fMRI to assist in evaluating health behaviours. Study Two aimed to use fMRI to evaluate physical activity, sedentary behaviour and glucose feedback obtained through wearable digital health technologies and to explore associations between activated brain regions and subsequent changes in behaviour. Study Three aimed to explore engagement of people at risk of type 2 diabetes using digital health technologies to monitor physical activity and glucose levels.

Methods: Study One was a systematic review of published studies investigating health messages relating to physical activity, sedentary behaviour, diet, smoking or alcohol consumption using fMRI. Study Two asked adults aged 30-60 years to undergo fMRI whilst presented personalised feedback on their physical activity, sedentary behaviour and glucose levels, following a 14-day wear protocol of an accelerometer, inclinometer and flash glucose monitor. Study Three was a six-week, three-armed randomised feasibility trial for individuals at moderate-to-high risk of developing type 2 diabetes. The study used commercially available wearable physical activity (Fitbit Charge 2) and flash glucose (Freestyle Libre) technologies. Group 1 were offered glucose feedback for 4 weeks followed by glucose plus physical activity feedback for 2 weeks (G_4GPA_2). Group 2 were offered physical activity feedback for 4 weeks

followed by glucose plus physical activity feedback for 2 weeks (PA_4GPA_2). Group 3 were offered glucose plus physical activity feedback for six weeks (GPA_6). The primary outcome for the study was engagement, measured objectively by time spent on the Fitbit app, LibreLink app (companion app for the Freestyle Libre) as well as the frequency of scanning the Freestyle Libre and syncing the Fitbit.

Results: For Study One, 18 studies were included in the systematic review and of those, 15 examined neurological responses to smoking related health messages. The remaining three studies examined health messages about diet (k=2) and physical activity (k=1). Areas of the prefrontal cortex and amygdala were most commonly activated with increased activation of the ventromedial prefrontal cortex predicting subsequent behaviour (e.g. smoking cessation). Study Two identified that presenting people with personalised feedback relating to interstitial glucose levels resulted in significantly more brain activation when compared with feedback on personalised movement behaviours (P<.001). Activations within regions of the prefrontal cortex were significantly greater for glucose feedback compared with feedback on personalised movement behaviours. Activation in the subgyral area was correlated with moderate-to-vigorous physical activity at follow-up (r=.392, P=.043). In Study Three, time spent on the LibreLink app significantly reduced for G_4GPA_2 and GPA_6 (week 1: 20.2±20 versus week 6: 9.4±14.6min/day, p=.007) and significantly fewer glucose scans were recorded (week 1: 9.2±5.1 versus week 6: 5.9±3.4 scans/day, p=.016). Similarly, Fitbit app usage significantly reduced (week 1: 7.1±3.8 versus week 6: 3.8±2.9min/day p=.003). The number of Fitbit syncs did not change significantly (week 1: 6.9±7.8 versus week 6: 6.5±10.2 syncs/day, p=.752).

Conclusions:

Study One highlighted the fact that thus far the field has focused on examining neurological responses to health messages using fMRI for smoking with important knowledge gaps in the neurological evaluation of health messages for other lifestyle behaviours. The prefrontal cortex and amygdala were most commonly activated in response to health messages. Using fMRI, Study Two was able to contribute to the knowledge gaps identified in Study One, with personalised glucose feedback resulting in a greater neurological response than personalised feedback on physical activity and sedentary behaviour. From this, Study Three found that individuals at risk of developing type 2 diabetes were able to engage with digital health technologies offering real-time feedback on behaviour and physiology, with engagement diminishing over time. Overall, this thesis demonstrates the potential for digital health technologies to play a key role in feedback paradigms relating to chronic disease prevention.

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"Alone we can do so little, together we can do so much."

– Helen Keller

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Dedications

I dedicate my thesis work to my family. Mum, Dad and Roxy, your endless support and energy to keep me going cannot be thanked enough. Words simply cannot express my appreciation, gratitude and love for you all.

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List of Abbreviations

ANCOVA, analysis of covariance

ATLAS, activity types from long-term accelerometric sensor data

BOLD, blood oxygen level-dependent

CPM, counts per minute

DBP, diastolic blood pressure

DKT, diabetes knowledge test

EEG, electroencephalography

e-HEALs, eHealth literacy scale

FDA, Food and Drug Administration

fMRI, functional magnetic resonance imaging

fNIRS, functional near infrared spectroscopy

GLM, general linear model

GPS, global positioning system

GUI, graphic user interface

HbA1c, glycated haemoglobin

HDL, high-density lipoprotein

IMD, index of multiple deprivation

METs, metabolic equivalents of task

mHealth, mobile health

mmol/L, millimoles per litre

MNI, Montreal Neurological Institute

mPFC, medial prefrontal cortex

MRI, magnetic resonance imaging

MVPA, moderate-to-vigorous physical activity

NDPP, National Diabetes Prevention Programme

NFC, near field communication

NHANES, National Health and Nutritional Examination Surveys

NHS, National Health Service

NMR, nuclear magnetic resonance

PA, physical activity

PRISMA-P, preferred reporting items for systematic review and meta-analysis protocols

PSA, public service announcement

ROI, region of interest

RPS-DD, risk perception survey for developing diabetes

SB, sedentary behaviour

SBP, systolic blood pressure

SD, standard deviation

SIGNAL, Sensing Interstitial Glucose to Nudge Active Lifestyles

T, tesla

TRI, technology readiness index

UK, United Kingdom

URL, uniform resource locator

US(A), United States (of America)

WFU (Pickatlas), Wake Forest University (Pickatlas)

Contributions

The author was responsible in collecting the data presented within the present thesis. Study One was conducted by the author with a colleague confirming papers to select for full text review. Study Two was conducted alongside another postgraduate student with responsibilities shared equally. However, the author was fully responsible for the fMRI component of Study Two; initially helping to make the fMRI setup functional at the NCSEM (which was previously absent) through to analysing the brain scans using MATLAB. The radiographers ensured that the scans were appropriately collected, and participants were safe to go inside the MRI scanner. Study Three was also the responsibility of the author with support from colleagues in confirming participant eligibility (as and when required). The author was involved in designing all three studies, putting forward documentation for ethical approval, assisting in recruitment, conducting health measures, deploying devices, collecting returned devices and completing data analyses. In addition, the author helped acquire funding (£2,550) to support Study Three. Dr Dale Esliger allocated funds to cover all remaining costs for the three studies. Continuous support was provided by Dr Dale Esliger, Dr Lauren Sherar and Professor Paul Morgan. Professor Paul Morgan contributed to studies one and two first and foremost because these aligned with his expertise.

Personal Achievements

Published journal articles

Whelan ME, Morgan PS, Sherar LB, Kingsnorth AP, Magistro D, Esliger DW. Brain Activation in Response to Personalized Behavioral and Physiological Feedback from Self-Monitoring Technology: Pilot Study. *Journal of Medical Internet Research* 2017;19(11): e384. DOI: 10.2196/jmir.8890

Whelan ME, Kingsnorth AP, Orme MW, Sherar LB, Esliger DW. Sensing interstitial glucose to nudge active lifestyles (SIGNAL): feasibility of combining novel self-monitoring technologies for persuasive behaviour change. *BMJ Open* 2017;7: e018282. DOI:10.1136/bmjopen-2017-018282.

Whelan ME, Morgan PS, Sherar LB, Orme MW, Esliger DW. Can functional magnetic resonance imaging studies help with the optimization of health messaging for lifestyle behaviour change? A systematic review. *Preventive Medicine*. 2017. 99. Pp 185–196. DOI: 10.1016/j.ypmed.2017.02.004.

Submitted journal article

Kingsnorth, AP; **Whelan, ME**; Sanders, JP; Sherar, LB; Esliger, DW. Sensing Interstitial Glucose to Nudge Active Lifestyles (SIGNAL): leveraging the physiological consequences of movement behaviours.

Conference oral presentations

Can functional MRI help optimise lifestyle behaviour change feedback from wearable technologies? *International Society of Behavioral Nutrition and Physical Activity (ISBNPA) Conference*, 7-10 June 2017.

Can fMRI help optimise lifestyle behaviour change feedback from wearable technologies? A pilot study. *Loughborough University Research Conference*, 31st October 2016.

Conference poster presentations

Can fMRI help optimise lifestyle behaviour change feedback from wearable technologies? *School of Sport, Exercise and Health Sciences Postgraduate Research Conference*, 14th June 2016.

Can fMRI help optimise lifestyle behaviour change feedback from wearable technologies? *The 2nd UCL Behaviour Change Conference*, University College London, 24-25th February 2016.

Can fMRI help optimise lifestyle behaviour change feedback from wearable technologies? A pilot study. *Loughborough University's Inspiring Research Conference*, 11 November 2015.

Awards

Winner in poster competition (*National Centre for Sport and Exercise Medicine- East Midlands Showcase Conference*) 2017

Shortlisted nominee for best oral presentation (*International Society of Behavioral Nutrition and Physical Activity (ISBNPA) Conference*) 2017

Runner-up in poster competition (*Loughborough University's Inspiring Research Conference*) 2015

Courses attended

Statistical Parametric Mapping (SPM) for Functional Magnetic Resonance Imaging Short Course; 19th-21st May 2016. University College London, UK.

Statistical Parametric Mapping (SPM) Course for Functional Magnetic Resonance Imaging; 16th-19th February 2016. University of Zurich and ETH Zurich, Switzerland.

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(February 2016).

Chapter One

Introduction and Literature Review

1.1. Introduction

There is a global prevalence of physical inactivity and sedentary behaviour (Kohl et al., 2012; Lee et al., 2012). Daily exposure to hypokinetic and obesogenic environments are in part contributing to their prevalence and resultantly are putting the UK (and global) population at risk of developing chronic diseases such as type 2 diabetes, hypertension and cardiovascular disease (Cardinal, 2016; Hamilton et al., 2008; Perrin et al., 2016). So much so, physical inactivity has been labelled the biggest public health concern of the 21st century and has been incorporated into the World Health Organisation targets for 2020 (Blair, 2009; World Health Organization, 2013b). In addition, physical inactivity causes substantial economic burden globally (Ding et al., 2016) with an estimated cost of $53.8 billion imposed on healthcare systems (Ding et al., 2016) and burdening the UK £1 billion annually (Allender et al., 2007). Adults spend an estimated 55% of the waking day sedentary (Matthews et al., 2008) or, put another way, adults spend 78 days each year sitting (British Heart Foundation, 2017); in part attributable to the number of potential chair opportunities met within 24 hours (Hamilton et al., 2008). In parallel, only 5% (Chaudhury & Esliger, 2008) or 13.5% of UK adults (Sport England, 2017) achieve the recommended physical activity guidelines. Therefore, more needs to be done to combat the prevalence of physical inactivity and sedentary behaviour (movement behaviours). A 2012 Lancet paper (Lee et al., 2012) acknowledged that adjusting population level rates of physical inactivity can deliver comparable global life expectancy benefits as to obesity (Olshansky et al., 2005) and smoking (National Research Council Committee on Population, 2011). This finding has added additional support (and urgency) to change movement behavioural patterns. Therefore, efforts to increase physical activity and minimise sedentary time to help counteract the continuing incidence of disease incidence are crucial moving forward.

Physical inactivity and sedentary behaviour are independent movement behaviours, yet they can (and often do) co-exist within each 24-hour period. This means that individuals can be highly sedentary, for instance by having an office-based job, yet be physically active, by achieving the weekly physical activity recommendations. Studies to date have investigated the health benefits of interrupting prolonged sedentary time with brief bouts of physical activity and observed promising results (e.g. Buman et al., 2014; Healy et al., 2015). However, the ill-effects of negative lifestyle behaviours (such as physical inactivity or prolonged sitting) are only perceived to impact us decades down the line. Therefore, it is a substantial and often overwhelming challenge to encourage people to act *today* to prevent the onset of chronic

disease *years or even decades later*. One way that might overcome this aligns well with continuing advancements in technologies that deliver personalised feedback. Behavioural monitoring technologies often present step count, laps swam, distance ran and, more recently, sitting time whilst physiological monitoring technologies can deliver feedback relating to heart rate, blood pressure and glucose levels. Delivering physiological and behavioural feedback may be one approach to help guide individuals to observe the acute benefits of positive behavioural decisions.

Efforts to date have included population-level and individual-level (personalised) health messages to inform and encourage individuals to be more physically active. Health messages are often targeted to specific audiences (Latimer et al., 2010); for instance, health messages can be positioned at specific locations to deliver point-of-decision prompts to help nudge individuals toward making positive choices. This could involve positioning health messages to encourage individuals to use the stairs rather than the escalator and have demonstrated short-term promise (Webb & Eves, 2005). The method of dissemination or communication is crucial to determine the level of effectiveness and this can be done using subjective and objective tools to observe impact on behaviour change. Additional efforts to explore the delivery of individual-level health messages via personalised feedback are also warranted.

A growing marketplace is for digital health technologies which has seen an influx of consumer interest. These technologies aim to provide personalised, real-time feedback via wearable devices worn at variable body positions and/or smartphone apps. With technological advancements increasing capability to more accurately detect movement (and physiology) and immediate data presentation, it is becoming more feasible to reveal feedback ‘at-a-glance’. One example would be within diabetes management, whereby individuals can receive real-time insight into their glucose levels via a continuous glucose monitor (Wagner et al., 2012). This technology hopes to minimise the occurrence of hypo- and hyper-glycaemic events and so improve individual adherence to maintaining good glucose regulation. To date, available technologies deliver step count, distance travelled, floors climbed, laps swam, estimated caloric expenditure and heart rate (Sanders et al., 2016). In combination with other physiological technologies, such as continuous glucose monitors, the prospect of delivering behavioural and physiological feedback in parallel is emerging. With individuals able to access feedback about their behaviour and health at their fingertips, the opportunity to observe this relationship in action may help guide individuals to make better immediate decisions. This would be on the basis that individuals are able to view the acute physiological benefit of a positive behavioural

decision using the personalised feedback displayed. However, it will be crucial to recognise how individuals receive (or absorb) the data and observe what challenges may be faced during use.

There are many challenges to delivering optimal feedback to individuals. Referring back to diabetes management, it is well acknowledged that the value assigned to a technology is highly dependent on the user having sufficient levels of literacy, education and motivation (International Diabetes Federation, 2009). For instance, individuals living with diabetes may be provided with a continuous glucose monitor but if they do not have sufficient levels of education to understand what the information means, they are very unlikely to benefit from accessing the information it provides. This aligns well with the need to graphically display information in a way that is informative and motivational to the user (Western et al., 2015). When exactly feedback should be delivered is another challenge given that it is not always appropriate for behaviour change. Sending insightful feedback at times when positive behaviours can occur would be ideal (and is increasingly available given advances in context-based technologies i.e. Loveday et al., 2016). Digital technologies can help disrupt undesirable habits (Hermsen et al., 2016) but current evidence remains inconclusive as to whether these habitual changes are sustained. Maintaining use beyond the *honeymoon* period, which is generally within six months for the majority of users (Ledger et al., 2014), is crucial to prevent devices from being placed in the sock drawer, never to be worn again. With a view to sustain technology use, efforts to revamp or identify how users engage (or interact) with these technologies may help sustain use. Approaches to deliver more persuasive (or potent) feedback are needed and it may be sensical to increase feedback resonance by making the behavioural feedback tie into its physiological consequence.

The aim of this thesis was to assess how people responded to information presented via digital health technologies and to observe whether people would change movement behaviours (physical activity) when presented behavioural and physiological feedback in parallel. More specifically, Study One provides a review of published research using functional magnetic resonance imaging (fMRI) to assess how people's brains respond to health messages about key lifestyle behaviours. Study Two targeted a research gap within fMRI to assess people's neural responses to personalised health messages relating to physical activity, sedentary behaviour and glucose levels. Study Three intervened on individuals identified at risk of developing type 2 diabetes. The six-week intervention involved two novel digital health technologies that presented real-time physiological and behavioural feedback.

1.2. Literature Review

1.2.1. Communicable and non-communicable diseases

Transition from communicable disease to non-communicable diseases

In the past century, the major cause of mortality has shifted from communicable diseases toward non-communicable diseases (NCDs). The term NCDs has been used since the first Global Burden of Disease study in 1990, alongside infectious (communicable) diseases and injuries (Murray et al., 1994). However, recommendations confirm the need to reframe NCDs to void the inclusion of "non" (which can promote confusion) and promote a sense of urgency (Allen & Feigl, 2017). Therefore, NCDs will hereon be referred to as chronic diseases. Chronic diseases or long-term diseases are a leading cause of adult mortality worldwide (World Health Organization, 2002), with 68% of 56 million cases accounted for by chronic diseases (World Health Organization, 2014). Many of these deaths, increasing by 14.1% from 2005 to 2015, are attributed to cardiovascular disease (in particular coronary heart disease and stroke), cancer, respiratory disease and diabetes (Global Burden of Disease, 2016) (Figure 1.1). The total number of mortality cases exceeds the number of deaths (14.4 million) attributed to infectious disease recorded in 1990 (Murray & Lopez, 1997b). Communicable diseases (such as cholera and chickenpox) were transmitted from one individual to another via bodily fluids, direct physical contact or were airborne; affecting many individuals. Similarly, chronic diseases affect people across all income groups and put men, women and children at risk in developed and developing countries (World Health Organization, 2005). The Chief Knowledge Officer to the National Health Service (NHS), Sir Muir Gray, outlined that chronic diseases occur because of unhealthy environments or unhealthy lifestyles with extended exposure likely resulting in disease later in life (Gray, 2015). With the rapid pace of globalisation (Beaglehole & Yach, 2003; Reubi, 2016), it is increasingly important to consider the widespread presence of chronic diseases. Projections estimate that mortality attributable to chronic disease will increase to 49.7 million cases in 2020 from 28.1 million in 1990 (Murray & Lopez, 1997a) or from 59% in 2002 to 69% in 2030 (Mathers & Loncar, 2006). Consequently, it is important to consider how targeted efforts can be made to challenge the increasing prevalence of chronic disease and, in the process, contribute to improvements in life expectancy and quality of life.

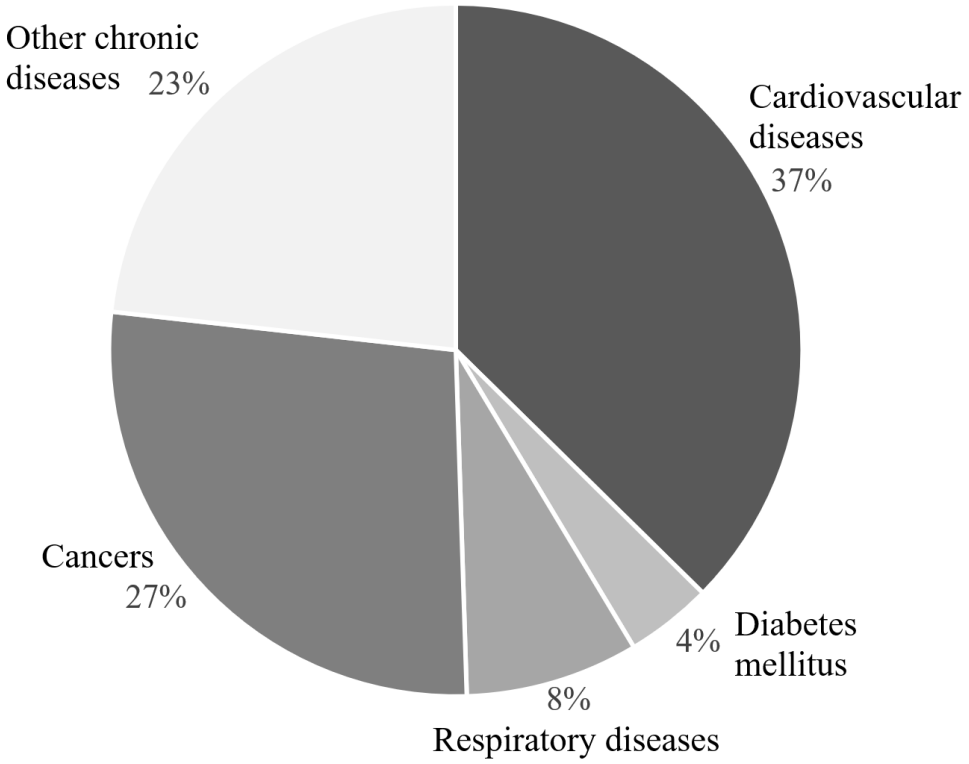

Figure 1.1. Proportion of deaths attributable to chronic diseases adapted from World Health Organization, 2014

Clinical forms of chronic disease

Cardiovascular diseases are ranked as the leading cause of mortality globally (Bauer et al., 2014) with approximately 17 million deaths recorded annually (World Health Organization, 2011a). Of these mortality cases, 42% were attributed to coronary heart disease. Coronary heart disease, resulting in a blockage to the heart's blood supply or an excessive accumulation of plaque, is a leading UK public health concern that costs the NHS £1.73 billion annually (Liu et al., 2002). The chronic condition generally affects men more frequently than women (11% versus 25%) as men demonstrate fewer favourable behaviours (e.g. energy intake, physical activity and non-smoking) and health factors (e.g. optimal blood lipids, blood pressure and glucose levels) (Mozaffarian et al., 2015). Given similarities between the UK and America, the prevalence of coronary heart disease will likely be comparable. Annually, more than 600,000 Americans experience a new coronary attack and more than 300,000 people experience a recurrent attack; demonstrating the importance of reducing its prevalence. With only 18% of Americans presenting at least five favourable cardiovascular health factors and benefits, it may come as no surprise that one in seven deaths were attributed to coronary heart disease in 2011

(Mozaffarian et al., 2015). Hypertension, or elevated blood pressure, has been attributed to 45% of coronary heart disease mortality cases. From 1990 to 2015, rates of elevated systolic blood pressure (and their estimated associated deaths) have substantially increased based on 844 studies across 154 countries (Forouzanfar et al., 2017). Hypertension is considered one of the most commonly treated conditions in the UK; affecting 26% and 31% of women and men, respectively (Health Survey for England, 2016). Hypertension has been identified as a leading risk factor that is attributable to 7% (6.2-7.7%) of global disease burden (Lim et al., 2013).

Diabetes (or diabetes mellitus) is one of four priority chronic diseases targeted for action (World Health Organisation, 2016). People living with diabetes are generally unable to adequately absorb glucose. This physiological restriction prevents circulating levels of glucose from freely entering appropriate sites (e.g. muscle tissue). Despite attributed to fewer deaths (i.e. 8.4% of all deaths for adults aged 20-79 years [International Diabetes Federation, 2013]), diabetes is one of the most prevalent chronic diseases. The global prevalence of diabetes has quadrupled between 1980 and 2014 with 382 million (8.3% of the world's population) diagnosed (International Diabetes Federation, 2013). Moreover, this number is expected to rise further to 592 million by 2035 (Guariguata et al., 2014). In the UK, there are approximately 3.2 million people living with diabetes (Health and Social Care Information Centre, 2013) at an estimated cost of £9.8 billion annually (Hex et al., 2012). There is also a large proportion of individuals (projected to be 174.8 million) who are living with undiagnosed diabetes (Beagley et al., 2014) who collectively account for 46% of current prevalence statistics (International Diabetes Federation, 2013). Approximately one quarter of American adults are living with undiagnosed diabetes (Menke et al., 2015). Type 2 diabetes frequently goes undiagnosed because of its gradual development and often the lack of immediate symptom manifestation, which leaves individuals unaware until classic symptoms present. The number of expected deaths aligned to the complications of diabetes is expected to double from 2005 to 2030 and an increased presence of diabetes complications occurring in adults aged 45-64 years (Gregg et al., 2016); requiring effective global action to halt the rise in diabetes prevalence (World Health Organisation, 2013). As a result, it is highly important to target efforts toward the prevention of diabetes.

Diabetes presents in one of three forms: type 1, type 2 or gestational with each presenting their own complications and negative health outcomes. However, due to sophisticated laboratory testing equipment, separate global prevalence statistics are unavailable (World Health Organisation, 2016). Briefly, type 1 diabetes has an unknown exact cause but is characterised

by insufficient insulin production and occurs most often in children and adolescents. Type 2 diabetes is often attributed to an interplay between metabolic and genetic factors and is characterised by inefficient use of insulin produced by the body. In comparison, gestational diabetes is temporary (occurs during pregnancy) and is associated with several factors, including but not limited to age, weight status and family history (World Health Organisation, 2016). Type 2 diabetes is most common accounting for approximately 90-95% of all diabetes cases (International Diabetes Federation, 2013). Consequently, as alluded to by Barry and colleagues (Barry et al., 2017), the management and prevention of type 2 diabetes has international priority moving forward.

Preclinical forms of chronic disease

Preventing the onset of chronic diseases is crucial and may in part be supported by recognising how lifestyle behaviours contribute. With projections estimating an increasing prevalence of chronic disease, efforts to identify individuals at risk of chronic disease is paramount. Individuals at high risk of developing diabetes (i.e. presenting the early stages of impaired insulin sensitivity and insulin resistance) represent an important target cohort for disease prevention (Soliman et al., 2014). Impaired glucose tolerance and impaired fasting glucose are the two forms of prediabetes with individuals exhibiting impaired glucose tolerance more likely to develop diabetes earlier compared with those living with impaired fasting glucose. From 2003 to 2011, prevalence of prediabetes increased from 11.6% to 35.3% in UK adults aged ≥16 years old (Mainous et al., 2014) and thus there is an impending influx who are likely to develop type 2 diabetes in the coming years unless early efforts to intervene are employed. Left undetected, an estimated 5-10% of people living with undiagnosed pre-diabetes progress annually onto type 2 diabetes (Bansal, 2015). Therefore, early detection of levels indicative of prediabetes is pivotal as it poses a negating effect on several human, social, medical and economical factors (Soliman et al., 2014). Prevention of chronic disease is also crucial in individuals living with multiple chronic diseases (i.e. comorbidities) with hypertension and diabetes in combination resulting in a magnitude of negative health issues. More specifically, having hypertension, a high body mass index, high glucose levels and/or high cholesterol resulted in 10.8 million deaths in a single year (Danaei et al., 2014). Clustering of risk factors can result in a diagnosis of metabolic syndrome. Metabolic syndrome is an important cluster of heart disease risk factors and has a 33% prevalence in US adults (Aguilar et al., 2015).

Screening and treatment for type 2 diabetes prevention

Barry and colleagues outlined two strategies to help identify people living with prediabetes; namely, screen and treat and population-wide approaches (Barry et al., 2017). Population-wide approaches involve the wide dissemination of materials to inform individuals about public health opportunities to positively change behaviour, by encouraging access to green spaces (e.g. walking at the local park) and transport (e.g. active commute). This far-reaching approach contrasts with screen and treat. Screen and treat initiatives generally assess fasting plasma glucose, glycated haemoglobin (HbA1c) or involve an oral glucose tolerance test. Each test is conducted by a healthcare professional with results compared to a threshold. For instance, prediabetes using HbA1c as the blood marker is classified as 5.7-6.4% by the American Diabetes Association (American Diabetes Association, 2015) or as 6-6.4% by the National Institute for Health and Clinical Excellence (National Institute for Health and Clinical Excellence, 2012). Accurately identifying individuals living with prediabetes is an imperative step for the identification of who best to intervene on. Alternative approaches can incorporate risk assessment surveys to capture a predicted level of risk. For instance, Gray and colleagues produced a Leicester Risk Assessment tool to identify those at high risk of impaired glucose regulation and type 2 diabetes (Gray et al., 2010). It involves individuals responding to questions about their age, ethnicity, gender, family history of diabetes, diagnosis of hypertension, waist circumference and body mass index. Asking individuals to accurately reveal their current waist circumference and/or body mass index may be unrealistic. However, these tools are enticing to use given their minimal cost (and burden) and they can help support the early detection of cases before complications arise (Harris et al., 2003). Therefore, these tools are more practical for population level screening efforts (Gray et al., 2010). In light of evidence relating to pre-diabetes, the four major risk factors identified for the development of chronic disease are tobacco use, alcohol consumption, poor dietary intake and physical inactivity (World Health Organization, 2015). An additional, emerging risk factor is the prevalence of time spent sedentary (Hamilton et al., 2016).

1.2.2. Lifestyle Risk Factors for Chronic Diseases

Physical Inactivity

Physical activity is a complex, multi-dimensional behaviour that varies according to the duration, regularity and intensity (i.e. light, moderate, vigorous, or a combination thereof) (Marschollek, 2013). Caspersen and colleagues defined activity as ‘any bodily movement

produced by skeletal muscle that results in energy expenditure' (Caspersen et al., 1985). A consensus was published in 2017 to help clarify differences (and encourage consistent terminology) between the various movement behaviours (Tremblay et al., 2017). Physical activity varies by intensity with vigorous intensity physical activity positioned at the higher end of energy expenditure in the movement continuum (Tremblay et al., 2010). Energy expenditure can be quantified by using metabolic equivalents of task (METS) and this indicator of intensity has been used to classify METS values to activities of daily living for adults aged 18-65 years (Ainsworth et al., 2011). This compendium was produced to help increase transparency and comparability of physical activities completed across studies using self-report methods.

Physical inactivity, in comparison, denotes individuals who do not achieve the recommended levels of physical activity. Current UK guidelines endorsed by the Chief Medical Officer were published in 2011 and segmented according to age; releasing guidance for early years (<5 years), children and young people (5-18 years old), adults (19-64 years old) and older adults (≥65 year olds) (UK Department of Health, 2011). These age-specific guidelines recommend that adults aged 19-64 years accumulate ≥150 minutes of moderate-to-vigorous intensity physical activity in continuous bouts of ≥10 minutes (or 75 minutes of vigorous physical activity weekly, or a combination thereof) per week (UK Department of Health, 2011). A national survey conducted in England demonstrated that only 6% and 4% of UK men and women (Chaudhury et al., 2008) or 13.5% of UK adults (Sport England, 2017) achieved the recommended levels of physical activity using objective tools. Similarly, Troiano and colleagues outlined that fewer than 5% of US adults obtain sufficient levels of physical activity using data from the 2003-2004 National Health and Nutritional Examination Survey (NHANES) (Troiano et al., 2008). These objectively measured cohort findings differ largely to physical activity levels quantified via questionnaires. For instance, the Health Survey for England (HSE) survey also captured self-reported levels of physical activity and observed that 39% and 29% of men and women, respectively, achieved the recommendations (Chaudhury et al., 2008). This discrepancy is likely attributable to the limitations related to self-reported approaches of data collection (e.g. social desirability bias) (Sallis & Saelens, 2000). In parallel with high levels of inactivity across the adult population, demographic variations are also observed with females and older people achieving greater levels of physical inactivity (Hallal et al., 2012). Findings from the UK Biobank study in over 100,000 participants support this by outlining an age-related decline of around 7.5% per decade in physical activity from those aged

45-54 to 75-79 years (Doherty et al., 2017). In addition, seminal research conducted in the 1950's (Morris et al., 1953) and the 1970's (Paffenbarger et al., 1970) highlighted significant occupational differences in physical activity levels and associated ill-effects on health outcomes. The authors identified that individuals who were least active during working hours exhibited an elevated risk for myocardial infarction and the development of atherosclerosis (Paffenbarger et al., 1970). Given its position as the fourth leading cause of death worldwide (Kohl et al., 2012) and being attributed to 9% of premature mortality cases worldwide (Lee et al., 2012). Overall, efforts to eliminate the prevalence of physical inactivity would have a significant impact by helping increase the world population's life expectancy by 0.68 years (Lee et al., 2012).

Estimating levels of physical activity using self-report methods is frequently employed with the distribution of questionnaires common. Self-report tools can provide valuable information pertaining to the context of activity completed. For instance, questionnaires can identify the type of activity carried out (e.g. cycling, swimming or walking). In addition, they are also able to collect environmental and psychosocial information, perceived time and intensity as well as the purpose of the activity completed (Troiano et al., 2014). However, as previously outlined, these methods can often reveal inaccurate data at an individual level (e.g. Chaudhury & Esliger, 2008). Within the HSE data, it must be acknowledged that the self-reported and objective data were not collected at an identical timepoint; however, the results are unlikely to be too dissimilar from usual behaviour and thus highlights a clear discrepancy between the two data sources. These differences may in part be attributed to participants offering socially-desirable responses (Sallis et al., 2000) by feeling inclined to overestimate time spent doing physical activity (Klesges et al., 1990). These inaccuracies may be minimised by shortening the recall period. For instance, having shortened the recall period to 24 hours, responses were within 3-10% of the doubly labelled water measures and within 1-3% of objectively measured activity and sedentary time (Matthews et al., 2017). Another limitation to self-reported tools eludes to participant capability to stating their accumulation of activity in bouts of ≥10 minutes, which can be difficult to recall. Despite these limitations, many large epidemiological studies employ a combination of self-reported tools and accelerometers (such as Doherty et al., 2017) to capture a comprehensive overview of participants' physical activity levels.

Using objective measurement tools to capture a more accurate assessment of physical activity are evermore important for population level physical activity surveillance programmes (Bauman et al., 2016). Objective tools are largely small, non-invasive and minimally intrusive

and worn during free-living settings (Chen & Bassett, 2005). With advancing sophistication of technology, objective tools (such as accelerometers) are becoming increasingly deployed in large physical activity epidemiological studies such as UK Biobank (Doherty et al., 2017). To date, these devices have been commonly used to monitor and quantify behaviour patterns (Allet et al., 2010) having been deployed to the waist and interpreted using cut-points (thresholds) to interpret movement intensity (e.g. Freedson et al., 1998). Accelerometers are now widely used to characterise physical activity (e.g. Troiano et al., 2014) and, when compared with self-report tools, accelerometers provide a direct assessment of physical activity (Prince et al., 2008). They provide a more comprehensive profile of physical activity, beyond the traditional step count delivered by pedometers (Bauman et al., 2016). However, accelerometers do have their limitations.

For instance, there is often a lack in consistency when reporting accelerometer data; in particular the methods used to clean and process data which limits transparency between studies (Esliger et al., 2005). In addition, differing device models and cut points limits the opportunity to compare estimates of national levels of physical activity over time (Bauman et al., 2016). Another limitation relates to device wear or compliance. Data from 2003-2004 NHANES, recorded that 60-86% of adults aged ≥20 years provided ≥4 valid days of accelerometer wear (Troiano et al., 2008). In an effort to improve compliance to device wear, and capture the full 24-hour period, many large epidemiological studies have started to deploy accelerometers at the wrist. For instance, UK Biobank demonstrated that 81% of participants wore the device for ≥150 hours of a possible 168 hours (and observed minimal differences between males and females (Doherty et al., 2017). Consequently, wrist-worn deployment may become the favoured approach with ongoing development and support for established thresholds. Emerging analytical techniques are beginning to provide more sensitive information about physical activity (Clark et al., 2017). Efforts to improve the quantification and characterisation of movement behaviours is crucial given that behaviours such as physical activity are multi-faceted.

Sedentary Behaviour

Sedentary behaviour is an independent construct to physical inactivity and has been gaining increasing recognition given its ubiquitous nature in modern society. Individuals can be both highly sedentary and physically active and these individuals have been called ‘active coach potatoes’ (Healy et al., 2008). Therefore, emphasising the difference between these two movement behaviours is crucial moving forward. Sedentary behaviour has been defined as ‘any

waking behaviour done while lying, reclining, sitting, or standing, with no ambulation, irrespective of energy expenditure' (Tremblay et al., 2017) and is positioned toward the lower end of energy expenditure (Tremblay et al., 2010). Common sedentary postures include sitting, lying and reclining (aligning with its translation; 'sedere' meaning to sit) (see Figure 1.2). Similarly to physical activity, UK guidelines have been produced for sedentary behaviour, which recommend adults to minimise time spent sedentary (Department of Health, 2011). Despite the fundamental role of human evolution and the need to move, data from the 2003-2004 NHANES survey identified that adults alarmingly spend 55% of their waking day sedentary (Matthews et al., 2008). Spending as much time as a whole working day seated offers deleterious effects at a population level and also compromises metabolic health (Healy et al., 2008). Knowing how a person accumulates sedentary behaviour and their physical activity status is important for their interaction with all-cause mortality.

An important question is whether sedentary behaviour has an association with health, independent of physical activity. Ekelund and colleagues published a harmonised meta-analysis of 16 studies observing associations between all-cause mortality and sitting time (Ekelund et al., 2016). In total, participants were followed up at 2-18.1 years and over 84,000 deaths were noted. Findings demonstrated that daily sitting was not associated with all-cause mortality in individuals identified as being in the most active physical activity quartile. Furthermore, individuals in the two lowest physical activity quartiles observed greater mortality rates (12-59%) than those who accumulated <4 hours/day and >35.5 MET-hr/week. However, when physical activity was at its highest (>35.5 MET-hr/week), individuals sitting <4 hour/day and >8 hour/day observed no increased risk of mortality (HR=1.04, CI95% 0.99-1.10) during follow up. This suggests that having a physically active lifestyle overrides the potential ill-health effects of being sedentary daily. This meta-analysis concludes that moderate intensity activities eliminate the risk of death but only attenuates risk of death for high levels of time spent watching television. In contrast, Katzmarzyk and colleagues demonstrated a dose-response association between siting time and all-cause and cardiovascular disease mortality, independent of leisure time physical activity (Katzmarzyk et al., 2009). This study requested participants to evaluate daily sitting time as 'almost none of the time' extending to 'almost most of the time', which limited their ability to offer a magnitude of time spent sedentary, but they concluded the need to minimise sedentary time. Overall, the notions of 'even a little is good, more is better' or 'something is better than nothing' could be applied to physical activity

guidance and ‘sit less, move more’ applies to sedentary behaviour (Blair et al., 1992; Lee, 2007).

Self-reported tools are also frequently used in sedentary behaviour research. In consideration of the hypokinetic society that we live in, and with a continual presence of labour-saving technology, sedentary pursuits such as television viewing, computer use and car-based commuting are increasingly familiar (Owen et al., 2010). Time spent watching the television has been widely used as an indicator of time spent sedentary during leisure time given that people are most often seated whilst watching a programme and it is a hugely popular sedentary pursuit (Dunstan et al., 2007; Hu et al., 2003). However, with an ever-increasing prevalence of emerging technologies at home, in the workplace and within the community, television viewing is no longer a good proxy of sedentary behaviour. As a result, it is crucial to begin designing questionnaires that can distinguish between different sedentary pursuits. For instance, screen versus non-screen sedentary time is one approach (Tremblay et al., 2017) and this could be further divided into time whilst using different screen-based devices such as tablets, laptops and smartphones (Stamatakis et al., 2013). A review conducted in 2017 identified interventions using digital tools to reduce sedentary time and observed that computer based mobile and wearable technologies appear promising (Stephenson et al., 2017). This emphasises the need to accurately capture sedentary time whilst using these technologies. Difficulties with this approach relate to the potential for over-reported time spent sedentary given that these sedentary pursuits can co-exist simultaneously (e.g. watching television whilst using a smartphone). Therefore, efforts are needed to help minimise this outcome. Identifying the specific domain of sedentary behaviour may help by requesting time within specific domains such as at work, during leisure time and whilst travelling (Marshall et al., 2010). However, similarly to physical activity measurement, it may be worthwhile investigating what objective tools are available.

Objective measurement tools to quantify sedentary behaviour vary given that posture rather than intensity is the primary component. Comparable to accelerometers, inclinometers are often small and lightweight in design. To date, many studies have used accelerometers to measure sedentary behaviour but they have been unable to distinguish between postures such as standing and sitting (Atkin et al., 2012). The consensus now confirms that sedentary behaviour measured using accelerometry should refer to stationary time given these devices are unable to determine posture, only intensity of movement (Tremblay et al., 2017). Inclinometers distinguish between different postures because of placement and tilt which helps identify interruptions or breaks in

time spent sedentary (Tremblay et al., 2017). In an effort to better quantify sedentary behaviour, inclinometers are becoming more abundant (e.g. ActivPAL) with acceleration and the angle of the thigh measured (Bassett et al., 2014). Similarly to accelerometers, recommendations suggest the deployment of inclinometers for ≥7 days and elude to 24-hour wear (Edwardson et al., 2016). Fewer models of inclinometer-based devices were available compared with accelerometers which has limited the quantity of free-living validation papers (Atkin et al., 2012). However, inclinometers and accelerometers are now being incorporated into single devices to help quantify both movement behaviours. These advancements in objective measurement tools highlight that they are increasingly able to accurately quantify movement behaviours (see Figure 1.2) in parallel to supplementary information gleaned from self-report tools.

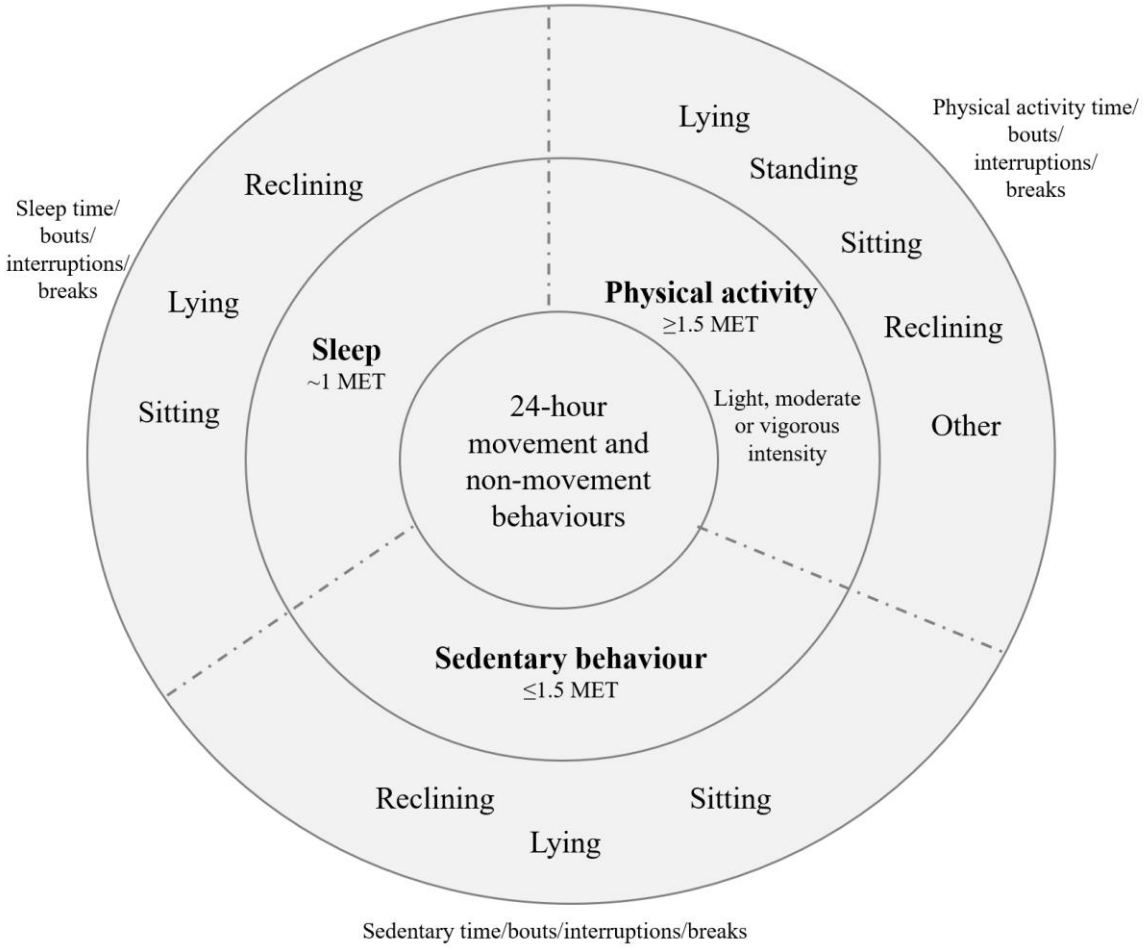

Figure 1.2. A framework of movement behaviours, adapted from Tremblay et al., 2017

Behavioural associations with chronic diseases

Physical activity associations with chronic disease

Strong evidence published in the 1990's suggested that physical activity was a significant factor in health promotion and disease prevention (Bouchard et al., 1993). This paper was further supported when physical activity was demonstrated to offer protection against incidents of coronary heart disease, hypertension, type 2 diabetes and result in improvements to insulin sensitivity (Shephard 1995). Physical activity toward the higher intensity end of the movement continuum has been shown to reduce resting blood pressure in normotensives, borderline hypertensives and hypertensives (Fagard & Tipton, 1994). Research conducted more recently continues to offer support that people achieving the minimum levels of physical activity are protected against hypertension (White et al., 2015), type 2 diabetes, cancer and cardiovascular disease (Warburton et al., 2006). The 2005-2006 NHANES data observed that physical activity was negatively associated with the metabolic syndrome and the major risk factors for chronic disease (Camhi et al., 2010). More specifically, with each additional 30 minutes of daily activity completed, 15% reductions to risk of developing metabolic syndrome were recorded (Camhi et al., 2010). The most compelling series of papers highlighting the associations of physical activity and chronic disease has to be the Lancet series published in 2012. Forming part of this collection of papers, Lee and colleagues revealed that physical inactivity was attributed to 6-10% of major chronic diseases including colon and breast cancer, coronary heart disease and type 2 diabetes worldwide (Lee et al., 2012). The paper also confirms that physical inactivity elucidates a similar effect to the ill-effects of tobacco consumption (National Research Council, 2011) and obesity (Olshansky et al., 2005). These findings were compelling and has provided momentum by increasing recognition toward physical inactivity as a major risk factor. Efforts must be made to better understand the reasons why physical activity can protect against the development of several chronic diseases.

Sedentary behaviour associations with chronic disease

An increasing body of epidemiological evidence suggests that sedentary behaviour is strongly associated with a number of adverse health outcomes (Katzmarzyk, 2010; Owen et al., 2010). To date, sedentary behaviour has been associated with metabolic syndrome (Healy et al., 2008), obesity (Jakes et al., 2003; Salmon et al., 2000), cardiovascular risk factors (Jakes et al., 2003; Thorp et al., 2010) and cardiovascular disease (Dunstan et al., 2010; Owen et al., 2010). Wijndaele and colleagues illustrated similar findings, having associated television viewing

with cardiovascular mortality with a hazard ratio of 1.08 over nine years (Wijndaele et al., 2011). The Nurse's Health Study identified that the relative risk for obesity and type 2 diabetes were 1.94 and 1.70, respectively, in those watching ≤40 hours/week compared with those only watching ≤1 hour/week of television (Hu et al., 2003). In contrast, findings from the Whitehall II cohort study described limited evidence linking incident diabetes with sitting time over 13 years (Stamatakis et al., 2017). These studies are in part limited by their employment of self-report tools to report sitting time. As previously outlined, using television as a proxy indicator for sedentary behaviour has been frequently used. Some literature, on the other hand, have focused on other domain-specific tools. When investigating time spent driving and during computer use, those in the upper quartile of time spent sedentary having a relative risk of 1.48 for developing incident hypertension (Beunza et al., 2007). Furthermore, as part of the Canada Fitness Survey consisting of 17,000 men and women, a clear dose-response relationship between sitting time and cardiovascular disease mortality was recorded, even after accounting for activity status and gender (Katzmarzyk et al., 2009). Despite offering context of movement behaviour, objective tools also reveal similar outcomes by associations with cardiovascular risk factors (Katzmarzyk, 2010) and cluster scores for metabolic risk factors (Healy et al., 2008) observed. An increasing number of smaller, empirical studies have been published that reveal the ill-effects of accumulating more sedentary time, with increases in cardiometabolic risk observed. However, no evidence supported mediation by change in waist circumference or BMI whereas larger reductions in waist circumference were associated with moderate-to-vigorous physical activity (Wijndaele et al., 2014). Therefore, to optimise prevention of chronic disease at a population level, it would be beneficial to target both the attainment of sufficient levels of physical activity and minimisation of prolonged sedentary behaviour in parallel.

Changing physical activity and sedentary behaviour to benefit health

Aforementioned evidence confirms that having greater levels of physical activity and reducing time spent sedentary (whether objectively or subjectively measured) can positively influence physiological markers. Given that lower activity levels have been associated with more abnormal blood glucose levels (Mainous et al., 2017), emphasising how people can achieve physiological benefits may be crucial. A Danish study observed that when healthy, active men reduced their ambulatory daily step count from 10,501 to 1,344 over a period of two weeks, impairments in metabolic markers (such as peripheral insulin sensitivity) were revealed (Krogh-Madsen et al., 2010). Similarly, asking participants to reduce their levels of physical activity to <5,000 steps over three days revealed reductions in cardiometabolic fitness (Mikus

et al., 2012). Another, albeit older, study demonstrated that differences between endurance runners and sedentary individuals for insulin sensitivity can be eliminated following 38-48 hours of exercise cessation (Burstein et al., 1985). In combination, these findings highlight that acute behavioural changes (over the course of several days) can have a marked effect on physiological mechanisms.

Similarly, marked effects on physiological outcomes have been observed when sedentary time has been investigated. Most often conducted in laboratory settings, empirical studies have deployed continuous glucose monitors (outlined in the next section) (DiPietro et al., 2013; Harris, 2001) and conducted frequent venous blood sampling (Dunstan et al., 2012; Peddie et al., 2013). Interestingly, these studies investigated the metabolic consequence of sitting (such as postprandial glucose and/or insulin) and imparted several conditions on participants. For instance, Dunstan and colleagues asked participants to undergo: (i) uninterrupted sitting, (ii) sitting with light-intensity walking and (iii) sitting with moderate-intensity (Dunstan et al., 2012). As outlined in Figure 1.3, the interrupted conditions had participants doing two minute bouts of continuous walking at 20-minute intervals over the course of the observation period. Their findings revealed lowered postprandial glucose and insulin levels within the interrupted sitting conditions. Other studies have found similar findings with regular, brief activity breaks reducing postprandial levels in normal weight (Peddie et al., 2013) as well as overweight and obese adults (Dunstan et al., 2012). However, there is a need to extend the exposure time beyond distinct days in a laboratory. Other studies have deployed monitoring devices over periods extending up to 48 hours (DiPietro et al., 2013; Harris, 2001). Another implication to this can be that individuals compensate their behaviours such that regularly interrupting sedentary behaviour during the working day may result in reductions to activity and/or increases in sitting time after work (Mansoubi et al., 2016). On the other hand, one hour of physical activity does not overcome the negative effect of physical inactivity if the rest of the day is spent sedentary (Duvivier et al., 2013). Given that prolonged sedentary time can offer different physiological consequences to those implicated with physical inactivity (Tremblay et al., 2010), it is clear that messages as to the importance of achieving both physical activity and sedentary behaviour recommendations are crucial to obtain health benefits.

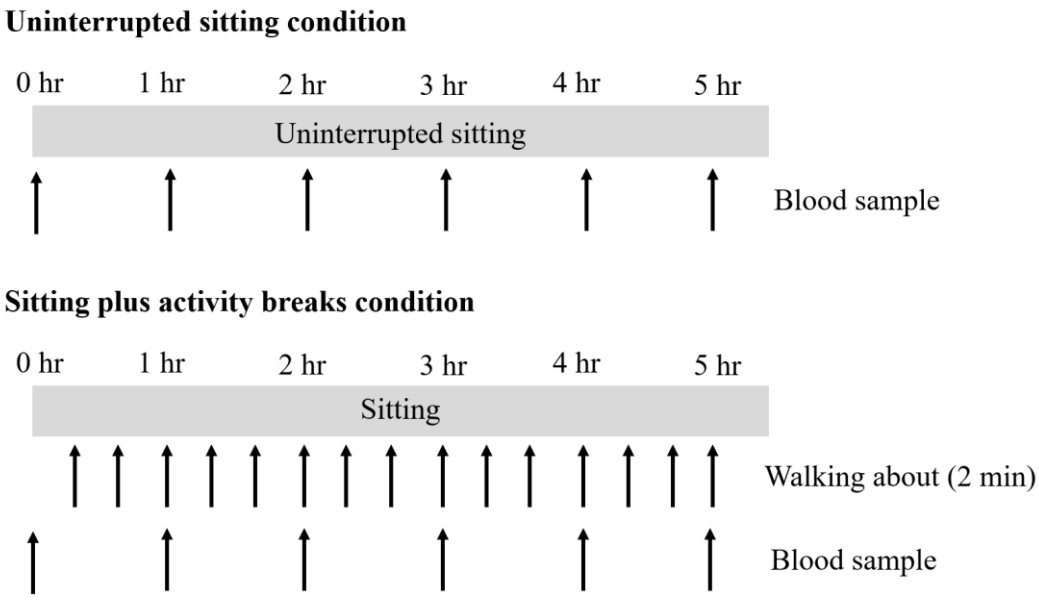

Figure 1.3. An example protocol to assess uninterrupted sitting with activity breaks, adapted from Dunstan et al., 2012

1.2.3. Commercial grade, wearable technologies

There are a multitude of health markers that can be monitored using commercially available technologies and given technological advancements, the volume and their capability will continue to expand. These devices are increasing able to quantify movement behaviours (physical activity and sedentary behaviour) and physiological markers. Devices aiming to quantify physical activity and/or sedentary behaviour have flooded the marketplace in recent years (Evenson et al., 2015; Sanders et al., 2016). Given the current ranking of chronic diseases and the need to prevent their onset, it is logical to first consider monitoring ambulatory blood pressure, given hypertension ranked as the most prevalent. However, wearable systems currently available are not yet optimal given the difficulty aligned with obtaining accurate readings (without being too cumbersome as a device to continually wear). In comparison, diabetes, which is ranked as the second most prevalent chronic disease, has an abundance of technologies available to quantify glucose levels which are continuing to advance. The three main technologies available to monitor glucose levels are: self-monitoring glucose, continuous glucose monitoring and flash glucose monitoring.

Monitoring physical activity and sedentary behaviour

The emerging market of commercial wearable technologies for quantifying human movement behaviours has been recognised as a leading trend (Ferguson et al., 2015) and have

subsequently encouraged their incorporation within research studies. The unflustered release of new devices, and the relatively slower rate of publication, can often restrict literature from maintaining pace with the marketplace. As a result, despite having the capacity to reach millions of people, their use within population level surveillance studies is restricted (Bauman et al., 2016). Consumer grade physical activity monitors, such as Fitbit and Garmin, appear increasingly capable of monitoring activities such as swimming (e.g. number of laps), cycling (e.g. distance covered) and resistance training (e.g. number of repetitions completed) which are often unclassified or misclassified by devices worn close to centre of mass. From a review conducted in 2016, a total of 146 technologies were identified as capable of monitoring sedentary time and/or physical activity (Sanders et al., 2016). Primarily marketed as tools to log or monitor movement behaviours and performance, these devices are engineered to be wearable to minimise device removal. Given their global position, these devices encourage real-world research by offering scalable prices and access 'off-the-shelf'. However, efforts must focus on testing health applications because the sheer volume suggests they are not reviewed prior to release (Powell et al., 2014). In addition, ensuring affordable technologies are used and comparable over time will be essential to capture national physical activity levels (Bauman et al., 2016).

The validity of these technologies have largely been assessed within laboratory settings; demonstrating a high correlation for indirect calorimetry with the Fitbit and Jawbone (independently, $r \geq 0.80$) for step count but over- and under-estimations were observed at slower and faster speeds, respectively (Evenson et al., 2016). Overall, high validity was observed for steps but low validity for quantifying sleep and energy expenditure (Evenson et al., 2016). Since this publication, however, the Jawbone has been retracted from the market which confirms that the industry is evolving rapidly and devices are often superseded with newer models (Bauman et al., 2016). Seven studies within the review reported on inter-device reliability and concluded a high inter-device reliability for steps, distance and energy expenditure (Evenson et al., 2016). Intra-device reliability, assessed by Dontje and colleagues, demonstrated good levels of agreement (at the minute, hour and day level) between ten identical Fitbit Ultra devices worn by one individual over eight consecutive days (Dontje et al., 2015). When compared with research grade devices (e.g. ActiGraph GT3X worn on the waist), the Fitbit Flex (wrist) tended to underestimate proportion of time spent sedentary and light intensity by 20% and 34%, respectively (Dominick et al., 2016). Observed variations between models and within models emphasises the importance of selecting an appropriate device.

Digital health technologies are also increasing likely to incorporate photoplethysmography into devices. Photoplethysmography relies on optical-based sensing using a pulse oximeter to identify light absorption and so record heart rate. Commonly deployed at the wrist, tightly linked to increasing wear-ability, these devices offer information pertaining to heart rate and movement behaviours to offer a more comprehensive profile. As with accelerometers and inclinometers, digital health technologies obtain a wealth of data which can result in differing analysis methods (Thompson & Batterham, 2013). Regardless of the objective measurement tool utilised, an understanding of self-report and objective measurement and respective positive and negative aspects should be considered (Allet et al., 2010).

Wearable devices provide convenient data collection, analysis and storage over extended periods of wear and, with increasing sophistication, reveal immediate feedback to the user (Mercer et al., 2016). They have been noted as appropriate tools to stimulate physical activity in people living with chronic disease in primary care (van der Weegen et al., 2013) and for public health and rehabilitation settings (Lyons et al., 2014). A review conducted by Conroy and colleagues identified that over 80% of the identified apps involved physical activity (Conroy et al., 2014). Another review demonstrated that interventions targeting overall daily reductions in sedentary time have largely used emails, websites and text messages (Stephenson et al., 2017); highlighting that more interventions using wearable technologies are warranted. Changing movement behaviours could be facilitated by wearable devices (Patel et al., 2015) with increases in physical activity observed when provided with devices that encouraged goal-setting (French et al., 2014) and self-regulation (Floegel et al., 2015). Given only a quarter of studies to date have incorporated these behaviour change techniques (Conroy et al., 2014), many wearable technologies (and their respective applications) need to begin incorporating principles from theories of health behaviour. Health-related behaviours, encouraged by wearable technologies, can improve population health but only if positive behaviours are sustained. Studies to date have largely varied in intervention duration, ranging from 5 days to 24 months (Stephenson et al., 2017). In another study, following three days of access to several commercial devices, participants (aged 52-84 years, living with ≥1 chronic disease) identified that these tools may be useful in promoting physical activity as a possible way to improve health (Mercer et al., 2016). However, future interventions targeting both physical activity and sedentary behaviour are warranted having recorded only 3 studies (Stephenson et al., 2017). Overall, wearable devices can help facilitate behaviour change but sustaining this is difficult

(Patel et al., 2015); therefore, it is intuitive that participant engagement with these technologies can help understand how people respond to the information presented.

Monitoring glucose levels

For people living with diabetes, it is crucial for these individuals to monitor changes in (blood/interstitial) glucose levels. There are three main tools used to capture this information and these include self-monitoring of blood glucose, continuous glucose monitoring and flash glucose monitoring (Figure 1.4). Self-monitoring of blood glucose has been a recognised and recommended, invasive technique to facilitate diabetes management for many years (International Diabetes Federation, 2009). The approach involves participants pricking their finger and using a handheld reader to measure glucose in the blood sample. Continuous and flash glucose monitoring tools, on the other hand, use disposable, minimally-invasive sensors that have a needle penetrating the skin. Both of these monitoring technologies calculate glucose levels using the relative concentration of glucose in the interstitial fluid, rather than blood glucose levels within capillary circulation and provide greater resolution compared with self-monitoring of blood glucose (Klonoff, 2005). Flash glucose monitors currently available are inserted into the left or right posterior brachium whilst the continuous monitors are often inserted into the abdomen. Continuous glucose monitors (e.g. Medtronic and iPro) have been suggested to help highlight pre-prandial, post-prandial and glucose levels during the night (Dungan, 2000) which still holds true nearly two decades later. Regardless of technological advancements and emerging techniques, all of these approaches can help, if used, to inform individuals of their fluctuating glucose levels which can, in turn, inform their treatment regime (e.g. when to take prescribed medication or how to manage dietary intake).

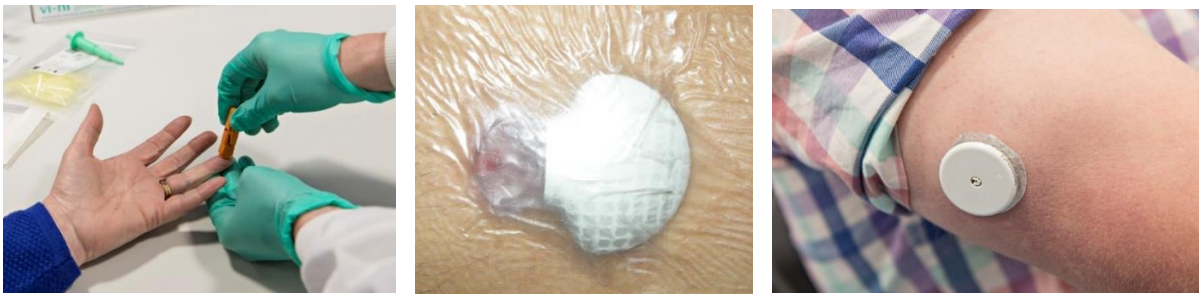

Figure 1.4. Examples of self-monitoring blood glucose (left), continuous glucose monitoring (middle) and flash glucose monitoring (right)

This provision of low, infrequent data can go some way in increasing user understanding and prompt the identification of patterns (e.g. magnitude of post-meal increases) (Inchiostro et al.,

2013). However, it is acknowledged that more frequent measures offer greater insight into daily glucose fluctuations (American Diabetes Association, 1994) and this guidance has not changed since the 1990's. However, even with multiple measures daily, self-monitoring blood glucose can only highlight the central tendency of glucose levels (Fonda et al., 2013) and subsequently fail to provide a complete glucose profile. As a result, many people living with diabetes raise concerns about how necessary these measures are given these limitations (Martin et al., 2006), and perceive these measures to not contribute to diabetes management (Polonsky et al., 2014) and so often fail to conduct enough measures to support them (Klonoff et al., 2008). With only 39% of individuals using insulin and fewer than 6% of individuals conducted self-monitoring blood glucose at least once daily (Harris, 2001), it is important to help promote regular readings for self-management.

In comparison, continuous and flash glucose monitoring technologies, given their similarities in information offered, may be perceived as less intrusive, with individuals able to limit their reliance on single, irregular measures (Pickup et al., 2015). With devices automatically recording regular readings daily (e.g. every 5-15 minutes), individuals are able to recognise patterns in glucose profiles and how movement and personal behaviours contribute (Bergenstal et al., 2013). However, there are limitations to consider when discussing these two technologies. Firstly, continuous glucose monitors have often required users to calibrate the reader which involves ≥1finger-prick sample each day (i.e. self-monitoring blood glucose) (Sacks et al., 2011). In an effort to overcome this, an expert panel of the US Food and Drug Administration have confirmed that the Dexcom G5, a CGM, can be sufficiently accurate and reliable for use without the need for calibrations (US Food and Drug Administration, 2016). In comparison, flash glucose monitoring devices are factory calibrated, meaning that they do not require people to conduct any finger-prick measures to function. Instead, the manufacturer advises users to finger-prick during times of rapidly changing glucose levels. Another limitation is that many individuals face psychological or financial barriers to using these forms of technology (Lodwig et al., 2014) and report sensor-related issues (e.g. 32% failed sensors) (Pickup et al., 2015). Due to the nature of monitoring interstitial glucose, results presented to the wear can often lag behind capillary blood glucose levels by 4.5±4.8mins (Bailey et al., 2015); likely attributed to the time required for glucose to diffuse into the tissues from the capillaries (Cengiz & Tamborlane, 2009). Despite these limitations, these advancing technologies offer consistent results (88.4% at day 2 and 85.2% at day 14) across wear (Bailey et al., 2015; Hoss et al., 2013), regardless of body mass index, age, type of diabetes, clinical

site, HbA1c or insulin therapy regime (Bailey et al., 2015). Consequently, with appropriate guidance and education, these tools may be beneficial for users to engage further with their health.

With greater exposure to information, individuals may feel more empowered (or competent) to make informed decisions for better self-regulation; aligning with the notion that individuals may feel better equipped to appreciate their current situation. Vigersky and colleagues demonstrated a significant 1% reduction in HbA1c% following three months in those individuals having access to continuous glucose monitors, compared with a 0.5% reduction in observed in the self-monitoring blood glucose group (Vigersky et al., 2012). This may be in part because individuals that engage more frequently with the feedback are better equipped to improve glucose control compared with people accessing the data less often (Fonda et al., 2013). Furthermore, these differences may be achieved because of greater exposure to the dynamic and temporal characteristics of continuous glucose monitoring (Kovatchev et al., 2015). Access to these technologies provides an opportunity for people to better manage glucose regulation by minimising levels of glucose variation (Rodbard, 2011). However, regardless of the frequency of accessing information, an adequate understanding is often a barrier in patients living with diabetes (Lodwig et al., 2014) and this still holds true today, especially with advancing sophistication of technologies. More specifically, the person wearing the device will be presented with information which may help them see the acute effects of behaviour on fluctuating glucose levels (Wagner et al., 2012). This process, termed temporal sequencing (Wagner et al., 2012), represents the identification and quantification of glucose levels in response to a given stimulus (e.g. consumption of food or bout of activity). Another approach prompted by Allen and colleagues highlighted that presenting individuals with another person's data resulted in increases in physical activity, decreases in sedentary time and improved HbA1c (Allen et al., 2009). This contrasts with the more common notion of personalised data being most potent (or persuasive), but another person's data is likely more potent than artificial data.

Figure 1.5 illustrates how continuous/flash glucose monitors capture fluctuating glucose levels over the course of 12 hours (in this example). In comparison, self-monitoring of blood glucose only captures three distinct measures with each of these within the target range. Only having access to the three distinct measures would miss the two 'high' and three 'low' events. That said, it is important to acknowledge that target ranges vary by context (e.g. upon waking, pre-meals and post-meals) as well as between people living with and without diabetes. It is

interesting to note that people living with diabetes aim to attain a flat line for their glucose whereas, in comparison, people living without diabetes observe largely fluctuating glucose levels across the 24-hour period. The target range is very important given its role in helping to identify high and low events. In Figure 1.5, the target range eludes to 2-hour postprandial glucose levels which may not be always relevant, so a dynamic target range may be more appropriate as technologies advance. As a result, it is advisable that these continuous glucose monitoring technologies become integrated tools to individuals living with diabetes (Fonda et al., 2013), which may help encourage routine behaviour with minimal (if any) restrictions imposed (Allet et al., 2010). Further investigation into how these technologies fare in samples of people at risk of (rather than diagnosed with) diabetes are warranted.

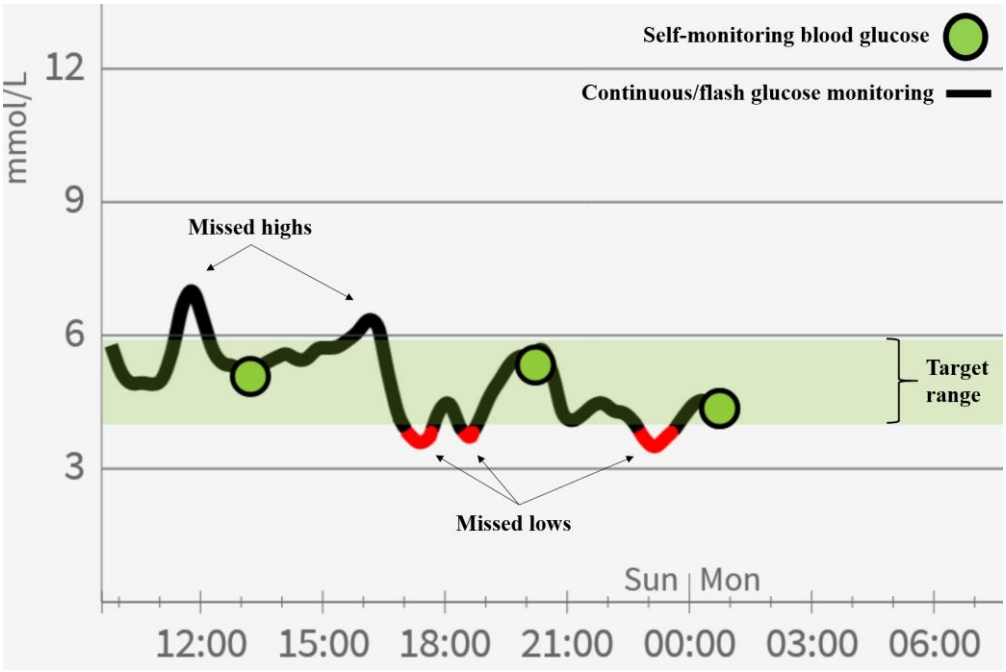

Figure 1.5. An illustration of the information that self-monitoring blood glucose can provide in comparison with continuous and flash glucose monitoring

1.2.4. Health Communication

Population level versus personalised health messages

Messaging is presenting information to large groups of people via media pathways such as television advertisements, print media, and the internet to a target audience (Latimer et al., 2010). Wide-reaching campaigns aim to encourage positive (and avert negative) behaviours within populations for health (Wakefield et al., 2010). Technology has provided the field of health communication with a platform to access large audiences (Cascio et al., 2013).

Population level health messages

The widely recognised public health campaign thus far for physical activity has been 'Change4Life', an NHS supported campaign targeting families to move more, eat well and live longer (UK Department of Health, 2009). Improving awareness to achieve physical activity recommendations and minimising time spent sedentary remains a substantial challenge with 82% of UK adults incorrectly recalling the national guidelines (Knox et al., 2013). Alternatively (or in addition) it may be attributable to individuals not receiving reasons why they should achieve these recommendations nor gain an understanding of how to achieve them (Latimer et al., 2010). This could be contributing to insufficient awareness about poor movement behavioural decisions and associated health implications. Others have highlighted that infographics, which attempt to draw a connection between healthcare professionals and the general public (Scott et al., 2016), may help display key information by largely using a visual format with key text included (Krum, 2013). Disseminating engaging messages is more likely when the behaviour targeted is episodic (or discrete) rather than habitual (Wakefield et al., 2010). As a result, encouraging people to change physical activity or time spent sedentary can be difficult. Another implication is whether messages should reveal the harms or the benefits (of physical activity and low time spent sedentary) is currently not fully decided (Wen & Wu, 2012). It has previously been suggested that loss-framed messages are best suited for screening whilst gain-framed messages for the prevention of behaviours (Rothman & Salovey, 1997). Despite this, a mixture of loss- and gain-framed messages have been utilised across the key lifestyle behaviours; highlighting uncertainty about which method is best for the prevention of chronic disease. For example, given the ongoing century long war on tobacco addiction (Fiore & Baker, 2009), the UK government enforced legislation necessitating cigarette companies to display health warnings on packaging (e.g. images representing blackened lungs and yellow teeth); aligning with a loss-framed message framework. However, uncertainty remains about whether population level messages should deliver highly threatening messages (e.g. risk of chronic disease) to encourage positive behaviour change, with evidence that these types of messages can result in increases in physical activity (Cho & Salmon, 2006). To assess awareness achieved for a given message, it is pivotal to conduct an evaluation to assess key outcomes including level of intention and whether change occurred (Bauman et al., 2006). Efforts have included the use of simple-to-understand language, using audio-visual formats and to tailor or personalise content to minimise issues surrounding health literacy (Barry et al., 2013; Mackert et al., 2014). Overall, it is important to consider how competent individuals in

terms of how able they feel to act on the health information being presented or provided to them. In an effort to support individuals with varying levels of competency, a broad range of health messages via number of modes (e.g. screen and non-screen based) are likely crucial to capture population-level attention. Consequently, it may be beneficial to deliver tailored messages (Appelboom et al., 2014) increasing resonance with the message.

Personalised health messages relating to movement behaviours

Pedometers have been the activity monitor of abundance in the past. However, with increasing sophistication, devices are increasingly able to quantify multiple aspects of activity with physical activity gaining recognition as a complicated behaviour (Thompson et al., 2015). Thompson and colleagues outlined that no single metric could truly classify level of physical activity and that tailoring of messages according to individual preferences as an optimal scenario (Thompson et al., 2015). Tailoring would encourage the presentation of specific metrics in relevant contexts and at specific times to help enhance the opportunity for behaviour change. Aligning with this approach, smartphone apps are a logical tool for behavioural interventions because they can monitor and classify behaviour almost immediately (Dennison et al., 2013). To date, step count has been rated as the most important metric by 74% of a national survey (n=1,349) with activity monitors considered helpful in promoting activity (Alley et al., 2016). Of the respondents, 63% stated that digital health technologies help individuals become more active (Alley et al., 2016). It must be acknowledged though that this sample of individuals may have been biased given that they have access to these devices and so may be more likely to be positive of their use. Another aspect is how messages are delivered to encourage a recommended quantity of behaviour. For instance, 41 people living with type 2 diabetes were randomised into one of two groups; scheduled to either receive advice about walking 30 min/day (at any time) or to walk 10 minutes three times per day (after each meal) (Reynolds et al., 2016). The findings were interesting; highlighting that advice to walk after meals was more effective in lowering post-prandial glycaemia; suggesting that aligning bouts of achievable activity around routine events helped participants achieve their advice. Delivering personalised feedback offers many challenges but it has the potential to deliver useful outcomes.

Personalised health messages relating to glucose

Other personalised health messages may focus on the physiological feedback. A position statement published in 2015 outlined that personalised (but comprehensive) approaches are

necessary and that displaying glucose patterns is a useful form of feedback (Powers et al., 2015). Encouraging regular monitoring is the crucial challenge with many life events or factors restricting the opportunity (e.g. diabetes severity, work commitments, physical activity and eating habits) (American Diabetes Association, 2015b). Another major concern is that a sufficient level of literacy is needed to accurately interpret the values presented to the individual (International Diabetes Federation, 2009). An inadequate level of health literacy has been associated with worsened glucose control in those living with type 2 diabetes (Schillinger et al., 2003), which reflects a potential lost opportunity to deliver useful information. Rowsell and colleagues identified that those with a higher level of health literacy perceived the information as easier to understand and found certain features motivating (Rowsell et al., 2015). This study investigated the use of a website which had participant accounts setup to access personalised information, restricting its reach for those who may have wanted greater, more immediate and easy access. The importance inflicted on having a sufficient literacy level to understand information means that education and training need to be provided (Battersby et al., 2010). It is important for healthcare professionals to understand the importance of individual understanding to optimise the opportunity to self-monitor. Healthcare professionals, such as specialist diabetes nurses, must consider individual literacy (International Diabetes Federation, 2009) because the transference of adequate knowledge is important (Klonoff, 2007) and, with individuals equipped with knowledge, patient empowerment can evolve (International Diabetes Federation, 2009). However, given the influx of technologies offering information on physiological markers, further consideration should be directed toward user knowledge and user comfort using mobile health (mHealth) platforms (Norman & Skinner, 2006). For instance, healthcare professionals should be able to conduct initial assessments (Driscoll & Young-Hyman, 2014) to ensure that all patients are sufficiently equipped and, where needed, they receive the guidance they need (Jarvis et al., 2010). This allows for the accurate deployment of advice to maintain an appropriate level of digital health use for diabetes management. However, further investigation into how individuals living at risk of (and not diagnosed with) chronic disease deal with physiological feedback would be warranted.

Temporal discounting

Temporal discounting refers to how people tend to discount rewards that are temporally distant because the delay weakens the value of the reward (Critchfield & Kollins, 2001). It has often been linked to monetary reward investigations and involves a hyperbolic discount function; meaning that the subjective value of a reward is reduced when there is time before the reward

is received. For instance, participants are often asked to decide between receiving an immediate payment and a larger payment, but they would receive the larger payment in the future. Similarly, in a sample of current, never- and former-smokers, Bickel and colleagues investigated how participants differed in receiving a specific quantity of cigarettes immediately or a greater quantity of cigarettes at a delayed time (Bickel et al., 1999). The authors identified that cigarette smoking was characterised by a loss of subjective value for delayed outcomes; meaning that current smokers were more inclined to take a more immediate (albeit smaller) reward. When alcohol was compared with money in a sample of active alcoholics, currently abstinent alcoholics and controls, alcohol was discounted more rapidly; meaning that rapid discounting of delayed rewards was observed (Petry, 2001). Therefore, an individual can be either impulsive (immediate gain) or self-controlled (delayed reward) (Bickel et al., 1999) and still holds true today. Regardless of the task under consideration, individuals must actively sustain a feeling of value for the rewards. Temporal discounting is a crucial theory to consider when encouraging behaviour change because the reward (e.g. optimal cardiometabolic health) can often be experienced in the distant future but is affected by decisions in the present. More specifically, a major challenge to improving population health is encouraging people to change their lifestyle behaviours today to improve health decades later. Figure 1.6 illustrates the concept by suggesting that individuals prioritise (or more greatly value) behaviours that offer immediate gratification, and poorly disregard those events that may occur later. With individuals often seeking the immediate gratification or reward to fulfil their need for value, encouraging positive lifestyle behaviours can be difficult to challenge. Given the nature of available technologies for type 2 diabetes, novel sensors are increasingly capable of delivering information about behaviour and physiological markers in parallel. Consequently, with perhaps enhanced levels of user interaction as a result of this additional angle to personalised feedback, it may help improve understanding about the effects of acute decisions on long-term health to lower the risk of chronic disease onset.

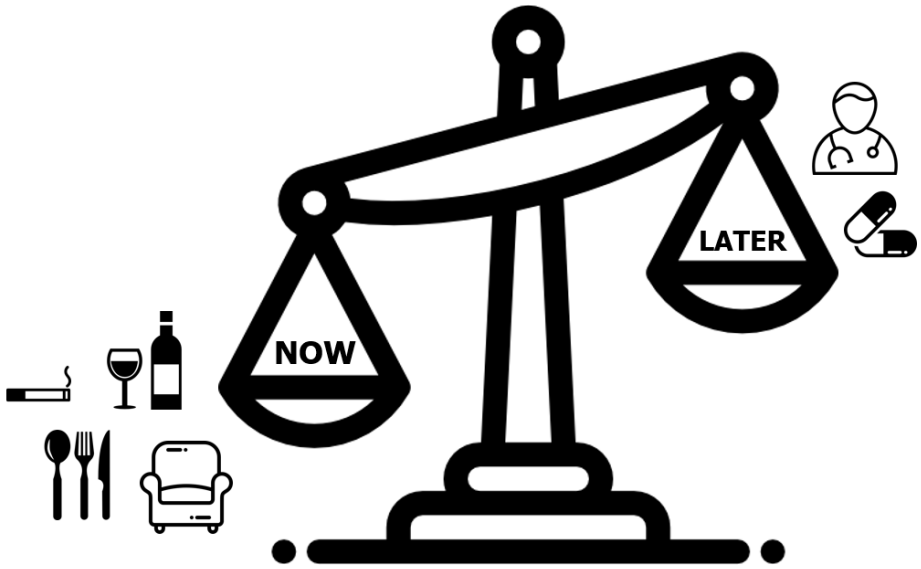

Figure 1.6. A schematic displaying how subjective value is highest in the present and lowest for events that may occur in the future

Assessing health messages

Interviews, focus groups and surveys offer valuable qualitative insight into individual preferences and perceptions toward feedback (about both content and delivery). Personalising health messages is crucial moving forward given the advances in digital health technologies. Previous research (Kreuter et al., 1999), which appears to still hold true today in other domains (e.g. Noble et al., 2015), demonstrated that tailored weight loss materials were significantly better than untailored messages. The materials that were investigated were tailored to an individual according to their response of a questionnaire; thereby limiting its potential given that question may have been misinterpreted or incorrectly answered. A systematic review published in 2010, containing ten studies, demonstrated that tailored information resulted in greater increases in physical activity compared with untailored material (Latimer et al., 2010); perhaps attributable to the materials resulting in greater resonance. If we can retrieve rich information regarding preferences for feedback, then we may be better positioned to reveal information pertaining to health and behaviour in a resonant way. Other studies employing qualitative methods have focused on disseminating road safety messages (Lewis et al., 2007), smoking whilst pregnant (Lewis et al., 2010) and obesity (Naughton et al., 2013). Although self-report tools provide valuable information concerning behaviour, there remains a large portion of variance unexplained; in part attributable to respondents providing socially desirable answers (Booth-Kewley et al., 2007), unconscious influences (de Camp Wilson & Nisbett, 1978), and a possible disconnect between responses provided in the laboratory and mental

processes that take place in the real world (Glassman et al., 2016; Klesges et al., 1990). Given these limitations, it is important to consider whether there is an opportunity to objectively assess how health messages are received.

1.2.5. Neuroimaging

One potential tool to objectively measure how health messages are received is neuroimaging under the umbrella of neuroscience. Neuroscience can be subdivided into several areas of interest. Communication neuroscience offers insight into understanding health communication (Falk, 2013) and helps bolster knowledge in nonverbal communication (Todorov et al., 2008); offering additional but supplementary information to traditional methods (e.g. focus groups). Communication neuroscience can be explored using an increasing number of available neuroimaging tools. These neuroimaging techniques can help identify what regions of the brain become activated whilst completing specific functions (or tasks) or processes; including emotion and affection, attention, social cognition, reasoning and language (Bookheimer, 2007; Cacioppo, 2002). The most commonly used neuroimaging techniques are electroencephalography (EEG), functional magnetic resonance imaging (fMRI), eye tracking and functional near infrared spectroscopy (fNIRS).

Neuroimaging tools

Electroencephalography, functional NIRS and event-related potentials

Despite the abundance of neuroimaging tools available, each neuroimaging tool offers respective positive and negative attributes. Electroencephalography records brain signals from the scalp and identifies changes in these signals along the spectral bands of delta, theta, alpha, beta and gamma. Because people are often unable or unwilling to justify or explain preferences when prompted, in part attributable to human behaviours driven by unconscious awareness (Calvert & Brammer, 2012), neuroimaging techniques can be crucial. Eye tracking, in contrast, measure eye movements which are considered the most frequent human behaviour (Bridgeman, 1992). Because the visual system provides an enormous amount of information, eye tracking is a key tool to try and understand what motivates people to act in certain ways. In previous years, eye tracking relied on direct observation of eye movements; limiting the measurement accuracy to the memory and accuracy of the observer (Dodge, 1906). The need to implement a better, objective record of eye movements using non-invasive methods was acknowledged (Dodge & Cline, 1901) and subsequent efforts evolved (Taylor, 1971). EEG and eye tracking are considered the least invasive neuroimaging tools yet still provide high

temporal resolution. fNIRS, despite measuring brain activation in a different way, does offer greater portability and relatively lower costs which may encourage investigations in more naturalistic environments.

Magnetic resonance imaging

Magnetic resonance imaging (MRI) has made a substantial contribution to neuroscience by permitting imaging of the brain. Its history lies in nuclear magnetic resonance (NMR) spectroscopy which largely relies on the angular momentum possessed by subatomic particles (i.e. protons, neutrons and electrons). Over time, NMR produced images using detection coils to align with the resonance frequency of hydrogen which was used to calculate water density. Given the prevalence of water in the human body, hydrogen is the most commonly studied element with MRI. Sir Peter Mansfield subsequently developed this approach further, producing methods to analyse these images and the approach later became known as MRI. Magnetic field strengths are typically 0.1-10T (tesla) and apply a strong magnetic field to align the spinning proton. The MRI scanner, such as the one shown in Figure 1.7 (MR750w 3T scanner [General Electric Healthcare, Chicago, IL, USA]), then produces a series of radio frequency currents to create a varying magnetic field. The protons absorb this energy and flip their direction of spin, which is maintained until the radiofrequency field is switched off. Upon switching off, the protons return to their normal spinning motion, and in the process, produces a radio signal. This returning to normal phase can be measured and subsequently made into an image through radio frequency coils. In relation to imaging anatomy, the MRI scanner distinguishes between differing tissue types by the speed at which the protons return to their normal spins. The loud noise anecdotally aligned to MRI scans is due to the constant flipping motion of magnetic fields. Unfortunately, because MRI uses magnets, individuals who possess any metal implants cannot go inside as they are not magnetic resonance safe and pose a hazard. MR images can be acquired with a range of image contrasts, such as T1, T2, or diffusion weightings, which indicate underlying structure. They may also be acquired with contrast dependent on physiological processes, such as blood flow, which can be manipulated to reveal angiographic information or functional MRI via the BOLD effect, as described below.

Figure 1.7. An MR750w 3T scanner (left) with a participant being prepared to go inside (right)

Functional magnetic resonance imaging

fMRI is a non-invasive neuroimaging technique that studies the brain whilst an individual completes a cognitive task inside an MRI scanner (Figure 1.7). More specifically, fMRI provides images that show the location of magnetic resonance signal changes associated with neural activity. fMRI works on the basis that a vascular change occurs when neural tissue is activated (Ogawa et al., 1990). Using a method called blood oxygen level-dependent (BOLD) contrast imaging, fMRI provides an indirect measure of neuro-electric activity (Logothetis et al., 2001). An early observation advocated that changes in neural activity resulted in signal changes that can take seconds to develop and decay (Bandettini, 1993). The theory behind BOLD contrasts is supported because deoxyhaemoglobin is paramagnetic in nature meaning it causes reductions in signal strength in the vasculature and surrounding tissue. Cerebral blood volume and blood flow increase when an area of the brain is activated; resulting in a lower oxygen extraction fraction of the blood. Blood supply demand is subsequently exceeded which causes a reduction in deoxyhaemoglobin. As deoxyhaemoglobin decreases, the paramagnetic properties are removed which results in a greater signal intensity. Therefore, an activated region of the brain demonstrates a more intense signal which can reveal a temporal measure of neural activity. This occurs after a haemodynamic filter has smoothed the pattern of activation which, in the process, can slightly delay signal production (Aguirre et al., 1998). While arterial blood is similar in its magnetic properties to tissue, deoxygenated blood is paramagnetic and so induces in-homogeneities within the magnetic field in tissue. As a result, the magnetic resonance imaging signal decays faster but signals from activated regions of cortex increase as the tissue becomes more magnetically uniform. Dynamic increases in volume and flow of

blood to an activated region of the brain, accompanied by changes in oxygen consumption, occur shortly after cognitive stimulation (Leniger-Follert & Lübbers, 1976). To localise these neural activations, low resolution images are acquired in rapid succession to produce mapped brain volumes every few seconds. In combination, these volumes produce a time-series of activation intensities for each voxel. fMRI produces relatively good spatial resolution with whole brain coverage, but the technique suffers from poor temporal resolution and issues surrounding reverse inference. Reverse inference suggests that activations of specific brain regions infer the engagement of a specific cognitive process which is not fully valid (Poldrack, 2006). There has been a recent expansion of interest in using fMRI as a neuroimaging tool bringing forward both scepticism and enthusiasm (Aue et al., 2009). However, having the capacity to measure specific cerebral structures in social cognition and behaviour has been noted as an outstanding achievement in contemporary neuroscience (Eisenberg, 1995).

Functional MRI, health messages and behaviour change

A systematic review conducted by Kaye and colleagues (Kaye et al., 2016) identified a variety of neuroimaging studies focusing on key human behaviours including smoking (Chua et al., 2011), nutrition (Kessels et al., 2011), sun safety (Falk et al., 2010), narcotic substances (Weber et al., 2015), safe sex (e.g. Seelig et al., 2014) and blood donation (Falk et al., 2010). The review identified twenty studies that employed event-related potential, functional near infrared spectroscopy or fMRI and demonstrated a growing body of research assessing visual stimuli. However, expanding the scope of the review to identify studies on other lifestyle behaviours may have revealed further studies. Lifestyle behaviour health messages are often disseminated on packaging to deter individuals or billboards to highlight health implications. Studies to date have compared persuasive and unpersuasive messages (Falk et al., 2010), tailored and untailored messages (Noar et al., 2007) as well as images of lifestyle behaviour (Jackson et al., 2014). Functional MRI studies often examine neural activation patterns in response to stimuli; offering insight into how people cortically respond. Understanding how messages can be made more potent (or persuasive) to encourage behaviour change is likely crucial. fMRI studies can also investigate human behaviour following exposure to a stimulus, such as health messages. For instance, after viewing anti-smoking advertisements, participants were subsequently measured at follow up for smoking consumption using exhaled carbon monoxide (a proxy indicator). Findings revealed that neural activity in response to anti-smoking advertisements accounted for 20% of the variance in how much exhaled carbon monoxide was recorded (i.e. how many were still smoking) (Falk et al., 2011). Moreover, the medial prefrontal cortex, a

region of the brain, acted as a surrogate marker for subsequent smoking cessation. In another study, using EEG, Versace and colleagues examined rates of smoking cessation and identified that neural patterns to emotional and smoking-related pictures had a role in predicting subsequent smoking cessation (Versace et al., 2011). More specifically, smokers with lower levels of neural activation in response to pleasant stimuli were less successful at ceasing smoking habits. These encouraging findings support the suggestion that social neuroscientists should examine new forms of media, such as social network sites and smartphones, to assess the role of technology in health communications (Cascio et al., 2013). The authors emphasise that people are affected differently by health message communications and subsequently act differently after exposure. However, in combination, neuroimaging tools (quantifying neural activity) and self-report surveys explain some variation related to behaviour change (Cascio et al., 2013). As a result, conducting more studies that employ objective measurements (using techniques such as fMRI) may be warranted.

1.2.6. Behaviour Change

Behaviour change framework

Behaviours are multi-dimensional and highly complex. Therefore, understanding how behaviours are influenced by both external and internal sources is important to develop interventions targeting change (Michie et al., 2013). The capability, opportunity, motivation and behaviour ('COM-B') model developed by Michie and colleagues suggests that a change in behaviour requires a change in one of the following: capability, opportunity or motivation (Michie et al., 2011). The former refers to the physical and psychological attributes to perform a behaviour (e.g. skill level), for instance personal ability to perform the behaviour. Opportunity eludes to external sources and can be social or physical; influencing how an individual engages with behaviour. For instance, it must be accessible and socially acceptable. The latter component is crucial and is comprised of reflective and automatic processes such as emotion, beliefs and goals. Motivation confirms that people must be highly driven to complete the behaviour. These three components of the COM-B model are interlinked such that increasing opportunity or capability can increase motivation. The Behaviour Change Wheel comprises the COM-B model along with nine intervention functions, including: education (e.g. knowledge and understanding), training (e.g. imparting skills) and enablement (e.g. reducing barriers/increasing means) (Michie et al., 2011). It offers a systematic and theoretically-based approach to help identify successful intervention types for a given behaviour and population.

Together, these functions are crucial to appreciate how these factors can be addressed in interventions targeting positive behaviour change in different contexts and populations (Glanz & Bishop, 2010; Michie et al., 2011). Interventions are now widely recommended to incorporate frameworks to inform behaviour change within the design and development phrases of a trial (Campbell et al., 2000) despite inconsistent findings relating to the effectiveness of incorporating theory into intervention development (Ammerman et al., 2002; Bhattarai et al., 2013). Overall, it is recommended to incorporate structure by using frameworks such as COM-B when deliberating how to design and deliver interventions targeting behaviour change.

Behaviour change techniques

Michie and colleagues identified that published interventions were reporting insufficient details relating to the key components within interventions (Michie et al., 2011). As a result, subsequent interventions have not been able to appreciate what ingredients could or should be included or avoided when in the design phase. As a result, the Behaviour Change Taxonomy was developed to help identify and classify the active content of the intervention directly focusing on the promotion of physical activity (Michie et al., 2013). The taxonomy has since helped to guide the standardisation of terminology and content across interventions in the field of behaviour change, having identified 93 active ingredients (organised into sixteen groups). Following the development of the taxonomy, Michie and colleagues assessed the effectiveness of behaviour change interventions equipped with the newly developed taxonomy (Michie et al., 2009). Moderator analysis identified that intervention effectiveness was directly related to the number of self-regulation techniques (e.g. self-monitoring) incorporated within these interventions. Of the 93 active ingredients identified by the taxonomy, the behaviour change techniques of feedback, self-monitoring and goal setting are most pertinent to this thesis.

Feedback and goal-setting

Feedback, defined as the opportunity to 'monitor and provide' information on performance of the behaviour or outcome (Michie et al., 2013), can relate to several topics within various settings. For instance, feedback can be offered in a visual, auditory, or tactile manner (Stone et al., 2005). Within an occupational setting, for example, aircraft pilots expect to receive sufficient, informative feedback to maintain accurate navigation and control of an aircraft. The cockpit is also designed to accommodate the pilot to minimise pilot error and any accidents (Lintern et al., 1999). Perhaps more applicable to the wider population, smart devices are now

more frequently found within UK households. These devices monitor energy consumption with the suggested aim of reducing monthly bill outlays simply by revealing real-time consumption (e.g. £0.21/hour). It has been suggested that this information can enhance user engagement (Daae & Boks, 2014). However, feedback must be appropriately presented to avoid negating the potential benefits of behaviour change (Hargreaves et al., 2010); perhaps in part attributable to levels of literacy toward numerical outputs and graphs (Hargreaves et al., 2010; Van Dam et al., 2010). Technologies targeted health and behaviour also have a role to play in encouraging change (Allet et al., 2010). A review conducted by Lewis and colleagues identified that interventions deploying wearable technologies found significant post-intervention increases in physical activity (24 days to 6 months) and reductions in sedentary behaviour (at 4 weeks to 3 months) (Lewis et al., 2015). However, how information is presented is crucial with level of motivation mediating the effect of the feedback received (Wood & Neal, 2007).

Use of traffic light colours and health target ranges have been identified as key approaches to help interpret data (Western et al., 2015). More complicated forms of feedback impose greater cognitive load which may negate its impact and likely reduce engagement (Hargreaves et al., 2010). The effect that feedback has on an individual and subsequent actions can be determined by personal intentions and goals set (Locke et al., 1968). If an individual lacks motivation to act upon the information or feedback received, then potency (or persuasiveness) can be reduced. However, receiving feedback can be a key technique because it provides information; previously demonstrated to surprise people or to reveal or misalign with what people think they achieve (Western et al., 2015). Feedback offered at an individual level is important, but it must be acknowledged there is no one-size-fits-all recommendation on how to present feedback on physical activity (Thompson et al., 2015). Integrating a dynamic but appropriate design is crucial for a successful behaviour change intervention. For instance, ensuring the graphic user interface (GUI) is interactive and resonates with the user. Related but independent to feedback is goal-setting, defined as to ‘set or agree on a goal’ to achieve a specific behaviour or outcome (Michie et al., 2013). As a key component of the widely recognised Control Theory (Carver & Scheier, 1982), goal-setting is a key ingredient to the action of self-management and control of behaviour. As a result, tailoring information has a crucial role in encouraging people to strive for, attain or exceed a target. However, ensuring that the target is dynamic is important as the user improves (or fails to reach) over time; minimising opportunity for de-motivation. Ideally, with increasing access to information from digital health technologies, there is a trend to move away from a physician-centred healthcare system (Battersby et al., 2010).

Self-monitoring

Michie and colleagues defined self-monitoring as a 'method for the person to monitor and record' behaviour and outcome(s) and as a key ingredient for behaviour change (Michie et al., 2013). With advancing technologies, people are increasingly able to see how they behave (e.g. time spent sedentary) but more needs to be done to demonstrate how immediate behavioural decisions acutely influence health. Also, with increasing sophistication, people can be prompted (or nudged) at specific times (e.g. every 30 minutes to prevent prolonged sedentary). However, consideration should be made toward the source of the information and the perceived level of expertise because these can be important indicators for information persuasiveness (Petty & Cacioppo, 1986). Gardner and colleagues reviewed and identified the active behaviour change techniques within numerous sedentary behaviour interventions (Gardner et al., 2016). Findings were considered particularly promising, with self-monitoring offering the highest promise ratio (measured the contribution of a behaviour change technique to the intervention output) of all techniques investigated (Gardner et al., 2016). This finding has been supported more recently in a systematic review that highlighted seven out of 17 interventions using self-monitoring of behaviour (Stephenson et al., 2017).

Given that digital health technologies such as a Fitbit offer a wealth of information, presenting the information in various forms such as numbers and graphs may help alleviate difficulties in understanding the content (Van Dam et al., 2012). Sanders and colleagues identified that over 90% of the 82 devices capable of self-monitoring sedentary time and/or physical activity revealed feedback in a numeric or graphic format (Sanders et al., 2016). Offering individuals with a visual representation of their behaviour and/or health can reinforce the information to the user (Kanfer & Goldstein, 1975). Previous pedometer-based study findings collated via a systematic review confirmed that simply providing users with a step count via a waist-worn device can increase physical activity levels (by 26.9%) from baseline levels (Bravata et al., 2007). In other contexts, self-monitoring of home energy consumption has identified 7-10% reductions when consumers were provided with smart meters to monitor energy usage (Wood & Newborough, 2003). Providing users with a source of immediate information can increase personal awareness toward what has been done and what is perhaps left to achieve. In general, interventions that employ self-monitoring in a synergistic manner, by combining self-monitoring with ≥1 other technique would result in greater effectiveness than when not incorporated in combination (Michie et al., 2009). Future studies should encourage accurate

reporting of behaviour change theories and how these were integrated in the intervention (Kitsiou et al., 2017).

Mobile Health (mHealth)

Consumer health wearables are considered the next 'Dr Google' (Piwek et al., 2016) whereby individuals often use devices to self-monitor and then visit healthcare professional equipped with personal information. These devices therefore offer the wearer direct access to personal analytics that can aid with prevention of chronic disease. There has been a recent rise in popularity for the use of both consumer activity or fitness monitors (Canalys, 2014) and smartphone apps (Pandey et al., 2013) contributing to the dynamic landscape of technology (Kelly, 2016; Patrick et al, 2016). These emerging tools allow continuous monitoring of movement behaviours (Case et al., 2015) but more could be done with regard to combining behavioural and physiological technologies. The rapid growth of digital technologies sector, in parallel with the evolving development of bite-sized technology and wearable devices, aims to deliver and supplement healthcare (Fiordelli et al., 2013) and subsequently promote behaviour change (Allet et al., 2010). The devices commonly make use of accelerometers (Preece et al., 2009) and conform to the notion of mobile health (mHealth). Given the widespread presence of unhealthy behaviours, many mHealth technologies aim to help individuals attain healthier habits (Klasnja & Pratt, 2014) which have potential to prevent or delay chronic disease. Devices are often located on the person (e.g. wrist-worn activity tracker) or situated at home (e.g. blood pressure monitoring). A recent review of systematic reviews identified 15 papers (52 unique studies) that focused on the effectiveness of mHealth interventions for the self-management of diabetes (Kitsiou et al., 2017); highlighting that diabetes has technologies available. Findings outlined a 0.8% improvement in Hba1c in the high quality reviews delivering mHealth interventions compared with standard care or non-mHealth approaches (Kitsiou et al., 2017). Further investigation is warranted to observe how these technologies may fare from a prevention perspective, for those living without (but at risk of) diabetes. Overall, these mHealth technologies align with the 'Quantified Self' movement (Swan, 2009) by enabling individuals to self-monitor behaviour and/or health.

Purchasing appealing commercial devices has flourished in part because of the reduction in costs with advancing expertise and expanding consumer interest. Providing the user with immediate feedback about behaviour on a convenient platform could be a fundamental motivator (Rollo et al., 2016). There is also an ever-increasing number of features monitored; for instance, sitting time, heart rate, and time spent active are common (Sanders et al., 2016).

These devices are able to gather and present continuous data in a small physical package (Culhane et al., 2005) which have since managed to downsize further. However, medical-related smartphone apps currently offer limited evidence (McCartney, 2013) and only borderline positive effects of technological interventions have been observed in over 8,000 participants (Alkhaldi et al., 2016). Rollo and colleagues identified that web-based programmes, smartphone apps and wearable devices all contribute to the self-management of chronic disease (Rollo et al., 2016); but more needs to be done in those living without chronic disease to observe whether these technologies can help prevent chronic disease onset. Considering the position of the device (e.g. wrist, chest or waist) and the frequency of charging is crucial (Rollo et al., 2016) as this will likely impact user compliance (Murphy, 2009). Similarly, smartphone apps provide push notifications, offer capacity to sync (link to transfer data) with multiple devices and are highly portable; however, restrictions on the use of a specific platform (e.g. compatible with Apple iOS) and developer costs (Rollo et al., 2016) are largely ignored. Luijkx and colleagues suggested that, provided with appropriate support and guidance, the older generation are also highly amenable to adopting new technologies (Luijkx et al., 2015). In combination, these findings support the use of mHealth within the whole population but incorporating mHealth into mainstream efforts must be implemented more quickly to maximise their benefits (Riley et al., 2015).

Engagement with mHealth

Engagement introduced

Engagement observes the quality of users' experiences with technology (O'Brien & Toms, 2008). Encouraging users to interact with mHealth or digital health technologies can often be a challenge. Considering there were an estimated 150,000 smartphone apps focused on health (Aitken, 2015), digital health technologies are increasingly promoted as a way to facilitate engagement with health (Steinhubl et al., 2013). Encouraging people to effectively engage with a tool can be viewed as more crucial than the act of engaging itself (Yardley et al., 2016); more specifically, engagement that leads to positive behaviour change is more important than the act of engagement itself. However, with only half of UK adults having immediate access to the internet via a personal mobile phone (McCartney, 2013) and greater engagement in those with higher education and income levels (Kohl et al., 2013), it is important to consider inequality divides. More recent evidence suggested that the proportions of households gaining internet access has been increasing annually, reaching an estimated 80% of coverage in 2013 (Dutton & Blank, 2015). Conflicting reports suggest that there are widening health inequalities

(indicator of socio-economic status) (McAuley, 2014) surpassing older research that recorded lower levels of health inequality (due to devices becoming more affordable and more accessible) (Muñoz, 2010). As a result, it is important to consider the digital divide and how varying levels of access to digital health (e.g. education, age, health status) impact how people access and engage with technology. However, it is also useful to acknowledge that all technologies tend to follow Gartner's hyper cycle of innovation (Linden & Fenn, 2003). The life cycle of any technology has been conceptualised with fast-track technologies taking approximately two to four years to cycle through the five stages. It begins with a pattern of excitement that evokes a great level of expectation (Figure 1.8), but with time and continuing mass media hype, it is common to observe negative experiences (e.g. supplier failures and negative press). Counteracting this potentially inevitable cycle emphasises the importance of producing technologies that supersede current items.

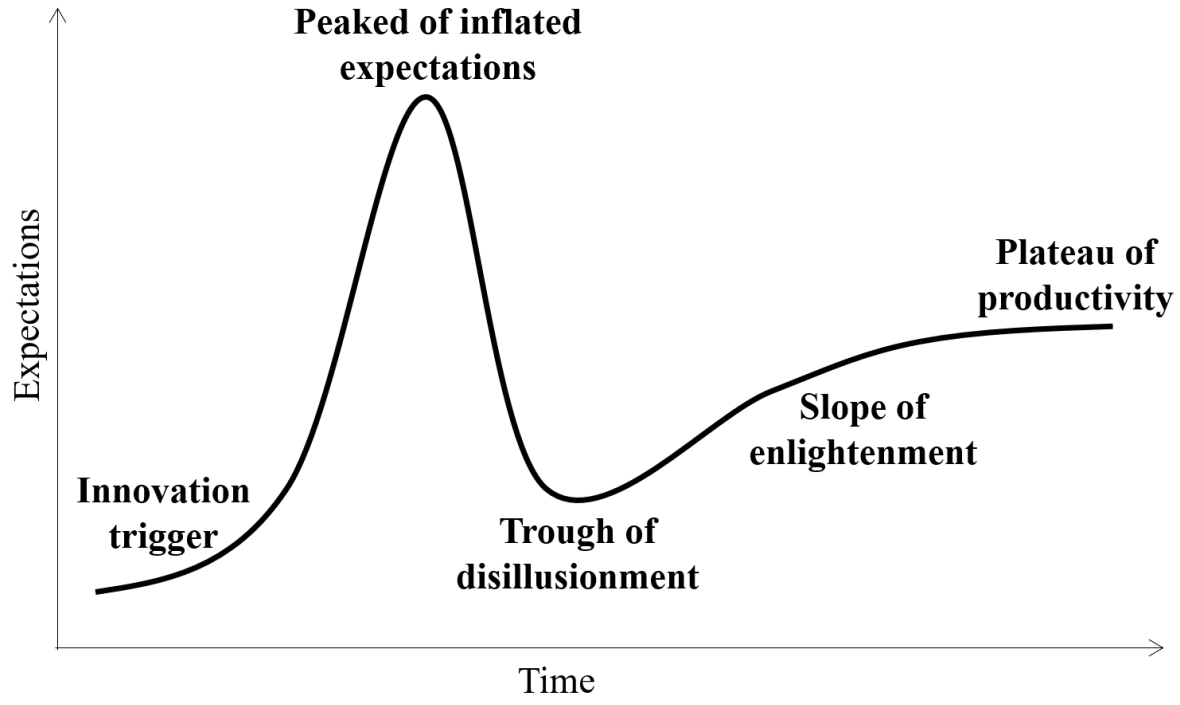

Figure 1.8. An illustration of the Hype Cycle of Innovation, adapted from Linden & Fenn, 2003

Concerns about engagement

Initial drive adoption and use of digital health technologies is complicated with questions raised about novelty (Ledger et al., 2014). A nine-item criteria has been produced to assess whether a device will be adopted and includes design, setup experience, form factor (how they fit), user experience and overall utility (Ledger et al., 2014). After overcoming the challenge of

accessing mHealth technologies, the subsequent hurdle involves encouraging long-term, sustained engagement. That said, it must be acknowledged that short-term use of these technologies may actually be appropriate for many (by being able to extract useful information quickly and not require longer-term wear) and so it would be inappropriate to expect long-term wear and engagement. Engagement can be evaluated using several tools, including: qualitative analyses, questionnaires, ecological momentary assessment, logs of system usage, sensors (within the technology) or by using psychophysiological measures such as fMRI (Yardley et al., 2016). There are a growing number of companies (e.g. Flurry Analytics) which, with permission, obtain data from the devices of interest (i.e. smartphone or wearable device) which can ease data capture and interpretation. Empirical evidence suggests that adoption and changes to motivation and behaviour are short-term (Klasnja et al., 2011). For instance, within a sample of 26 students aged 20-24 years, 65% of participants stopped using their Fitbit after only two weeks of use (Shih et al., 2015). Qualitative investigation identified that cessation of use was often attributed to: forgetting to put the device on, negative perceptions of device design as well as concerns for data management and accuracy (Shih et al., 2015). Poor long-term use has also been highlighted elsewhere with approximately one third of US consumers failing to continue using a device six months following purchase (Ledger et al., 2014). Conflicting findings were highlighted in a review conducted by Lewis and colleagues which identified that seven of eleven studies reported a retention rate of ≥80% (Lewis et al., 2015). This could be attributed to the context of having the devices deployed within a research setting (eluding to recruitment bias or heightened motivation to maintain adherence) rather than a real-world setting where perhaps there is minimal (or no) expectation for sustained use. Therefore, efforts to extend longevity of these devices in a real-world setting are warranted. Another concern relates to non-usage attrition where the use of mHealth is discontinued (i.e. users may still have access to the device but fail to use it). Eysenbach's Law of Attrition supports that attrition can be common within the context of mHealth because users have flexibility and choice to choose their *intervention dose*. More specifically, users are able to decide when or when not to wear the device as well their frequency of looking at it; supporting that non-usage attrition should be monitored and better understood (Eysenbach, 2005). For instance, in an intervention enrolling 4,378 individuals, only 20% were classified as active users. Reasons for the lack of sustained use or attention could include the following factors: insufficient encouragement from healthcare professionals, insufficient evidence relating to effectiveness, concerns about security and privacy (Birnbaum et al., 2015) or that the information fails to resonate (Aitken,

2015). Simply put, many users are not likely making full use of these technologies (Birnbaum et al., 2015) and efforts to combat this are warranted moving forward.

Measuring engagement

O'Brien and colleagues proposed a model of engagement (Figure 1.9) which outlines the process starting from the initial point of engagement to disengagement (O'Brien et al., 2008). Items contributing at the point of engagement include aesthetics, novelty, interest and motivation. During engagement, factors include aesthetic and sensory appeal, attention and awareness (and can appear and disappear over wear) whilst the point of disengagement can be attributed to usability, challenge and positive/negative affect. These attributes are highly changeable over time which demonstrates that engagement is a dynamic process varying both between and within subjects. Measuring engagement will largely vary between studies because of the varying types of technology employed and so often proxy metrics are used. Proxy metrics could involve the number of visits (or uses), number of features used, time spent on the intervention item, number (and type) of pages visited, and/or response to alerts or reminders (Brindal et al., 2012). In parallel, qualitative insights may include perceptions toward how useful the information was perceived (Schneider et al., 2016). Engaging with digital health technologies could be enhanced by presenting information *just in time* by capitalising on embedded sensors (e.g. global positioning systems or GPS) (Spruijt-Metz et al., 2015), tailoring the information source or demonstrating clear boundaries (Rollo et al., 2016). Alternate approaches include increasing individuals' involvement in the design of the technologies (Baker et al., 2014; Birnbaum et al., 2015) and encourage effective engagement, which has been defined as engagement sufficient to achieve intended outcomes (Yardley et al., 2016). Overall, it is crucial to gain insight into technology usage and user preferences in all activities to help identify how users interact with device interfaces which may encourage the release of more potent graphic user interfaces (Gero & Kannengiesser, 2009).

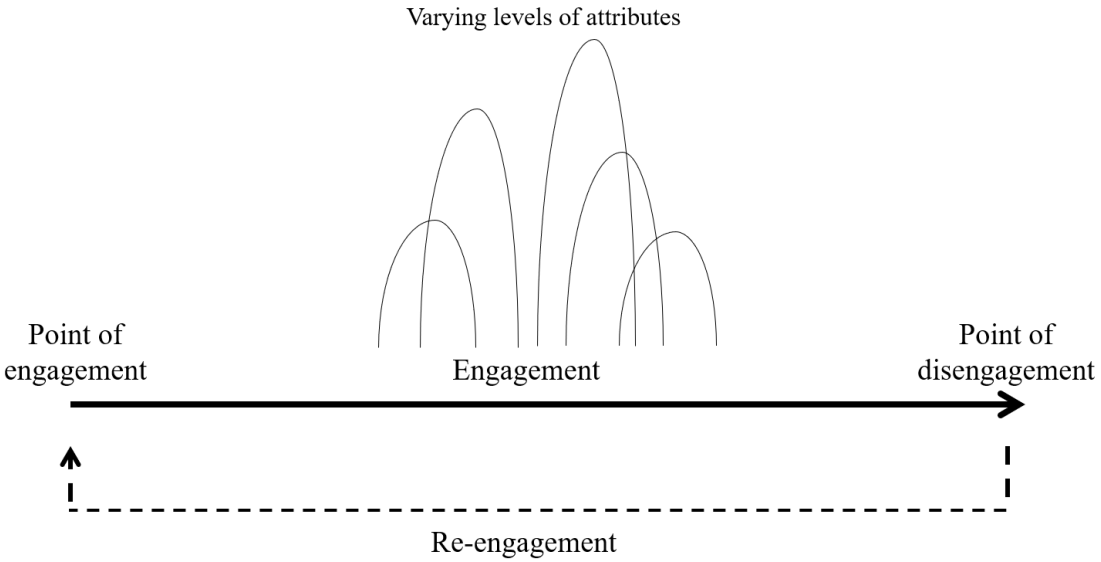

Figure 1.9. Proposed model of engagement, adapted from O'Brien & Toms, 2008

1.2.7. Bio-behavioural Feedback

Bio-behavioural feedback is a term coined to represent the simultaneous presentation of physiological and behavioural information. Examples of physiological streams include interstitial glucose, blood pressure and heart rate whilst examples of movement behavioural signals relate to physical activity and sedentary behaviour. It is becoming more feasible to measure physical activity in research focused on monitoring human physiology (Wright et al., 2017). Bio-behavioural feedback aligns well with the approach of 'teaching events' outlined and researched by Allen and colleagues (Allen et al., 2009). Teaching events represent occurrences where a distinct stimulus has an identifiable effect. Having the opportunity to present real-time feedback about physiology and behaviour in parallel may help the user understand the consequences of movement behaviours on their health. Identifying these teaching events can, more specifically, allow individuals to recognise the benefits of the stimulus (e.g. the positive impact a short walk can have on post-prandial glucose response) which may enhance the likelihood of the positive behaviour being repeated in the future. Individuals who accurately identify and interpret these events can positively modify both their behavioural and psychosocial status (Jarvis et al., 2010). Therefore, given the advancement in digital health technologies, providing individuals with more comprehensive feedback about their health and behaviour concurrently is becoming more feasible. Of course, efforts to appreciate how this information is delivered and understood are certainly warranted. Strategies such as these are likely paramount to begin to understand and integrate this approach of self-

monitoring into chronic disease management (Chiauzzi et al., 2015) and prevention of chronic disease. Given that current efforts to increase population level physical activity levels have been largely unsuccessful with insufficient levels recorded (Sport England, 2017), novel approaches to contribute to improvements should be encouraged. To date, an important limitation of the efforts to encourage people to be more physically active has been the assumption that we are willing to change our lifestyles *today* to reduce risk of developing disease *20 years* from now (aligning with behavioural discounting). This means that it can be difficult for individuals to appreciate the health benefits from being physically active which are subsequently observed years, or even decades later. However, with the notion of providing complementary feedback streams in parallel, there may be potential to illuminate the relationship between behaviour and health consequences which may empower individuals to identify these events and adjust future decisions. Overall, investigating whether bio-behavioural feedback could increase the persuasiveness (or potency) of the feedback by linking behaviours to acute health is a promising area for the prevention of chronic disease.

1.2.8. Summary

There is a global pandemic with physical inactivity and prolonged time spent sedentary evoking ill-effects on cardiometabolic health. Disseminating persuasive health messages is key to bolstering healthy lifestyle behaviours with a view to preventing and treating chronic diseases. With the ongoing influx of commercially available digital health technologies flooding the marketplace, it is crucial that the content that is being presented on smartphone apps (and the devices themselves) are critically assessed. Assessing these 'at-a-glance' health messages may help provide insight into how these forms of information (or feedback) are being received and whether they encourage positive lifestyle behaviour change. Neuroimaging techniques (such as fMRI) may offer a non-invasive, objective approach to measure how peoples' brains respond to personalised feedback delivered by digital health technologies. In addition, given that digital health technologies often experience attrition, it is crucial for researchers and the industry to try and understand how to increase sustained device use. One way may be to increase the potency (resonance) of the feedback being presented to users, which may be achieved by delivering physiological and behavioural feedback in combination. Delivering this enhanced form of feedback may help highlight events where behaviour has a noticeable, acute effect on health which may translate into behaviour change. However, efforts to identify how users engage with this form of feedback are warranted.

1.3. Thesis Aims

Study One

To review research using functional magnetic resonance imaging to assess how people's brains respond to health messages relating to physical activity, sedentary behaviour, diet, smoking and alcohol.

Study Two

To identify regions of the brain activated in response to personalised health messages relating to physical activity, sedentary behaviour and glucose control and subsequent behaviour change and how this relates to patterns of neural activation.

Study Three

To assess participant engagement, as a proxy for measuring potency, using novel physical activity and glucose technologies.

Chapter Two

Study One:

Can functional magnetic resonance imaging studies help with the optimisation of health messaging for lifestyle behaviour change? A systematic review

Whelan, ME; Morgan, PS; Sherar, LB; Orme, MW; Esliger, DW. Can functional magnetic resonance imaging studies help with the optimisation of health messaging for lifestyle behaviour change? A systematic review. *Preventive Medicine*. 2017; 99, pp 185-196.

Appendix A. Original publication has been adapted to fit within this thesis.

DOI: 10.1016/j.ypmed.2017.02.004.

2.1. Introduction

Chronic diseases such as cardiovascular disease, cancers and type 2 diabetes account for 60% of all deaths worldwide (Warburton et al., 2006). The onset of more than two thirds of all new cases of chronic disease is widely attributed to four modifiable risk factors; smoking, excessive alcohol consumption, poor nutritional intake and physical inactivity (Beaglehole et al., 2011). The prevalence for each of these risk factors is staggering with one in five UK adults current cigarette smokers (Office for National Statistics, 2016), over 85,000 alcohol-related deaths annually (Centers for Disease Control and Prevention, 2013), a rising global body mass index (NCD Risk Factor Collaboration, 2016) and only 5% of UK (Chaudhury et al., 2008) and US (Troiano et al., 2008) adults achieving national guidelines. This highlights that effective interventions to promote healthy lifestyles are needed. One approach that has been widely used is public health messaging which has the important advantage of reaching the population.

Promoting lower sugar intake, regular physical activity (e.g. 'Change4Life'), smoking cessation (e.g. 'Smoke Free') and minimising excessive alcohol consumption (e.g. 'Know your limits') are common aims of public health campaigns. In addition to these campaigns, point-of-decision prompts (e.g. take the stairs) and on-product packaging (e.g. 'Smoking Kills') also present persuasive micro-level messages which can also reach a wide audience. In particular, pictures of tar-filled lungs and yellow teeth are now commonplace on cigarette packages (World Health Organisation, 2009). These prompts are attributed in part to the reductions in smoking prevalence (Emery et al., 2012; Wakefield et al., 2010). However, ensuring campaigns and the information or images provided are impactful and evidence-based is crucial when implementing these behaviour change approaches (Latimer-Cheung et al., 2013). Therefore, to help ensure public health campaigns and point-of-decision prompts are given the greatest chance to change behaviour, it is important to assess how people respond to them.

Lifestyle behaviours are influenced not only by conscious choices (e.g. choosing to actively commute to work) but also by subconscious responses to the environment and stimuli (e.g. emotional responses to a television advertisement or billboard). For a decision to be made by the brain, self-related processing must occur which involves the evaluation of environmental stimuli with regards to its personal relevance. Given this, neuroimaging can provide valuable insight into subconscious responses to stimuli by examining regions of the brain and levels of brain activation when individuals view health-related messages. These insights may then be used to bolster the persuasiveness of health messages (Nisbett & Wilson, 1977) and as a result, increase the likelihood of changing behaviour (Kaye et al., 2016). Previous research has

highlighted that regions within the medial prefrontal cortex of the brain are associated with self-related processing (Lieberman, 2010) with people subsequently reducing time spent sitting when activations within the ventromedial prefrontal cortex were observed (Falk et al., 2015). Predicting behaviour change based on neural activity through functional magnetic resonance imaging (fMRI) offers an interesting brain-behaviour link (Falk et al., 2011); highlighting the importance of optimising the content of health messages as they have a direct effect on how people's brains engage with the health message and whether they ultimately change their behaviour. By producing and disseminating health messages that activate brain regions linked with successful behaviour change, health campaigns may have greater population-level success and be more cost-effective (Falk et al., 2010, 2011). The present review aimed to review studies that used fMRI to examine brain activity in response to health messages pertaining to physical activity, sedentary behaviour, dietary intake, smoking and alcohol consumption.

2.2. Aims and objectives

The aims of the review were to (i) examine stimuli content and modality; (ii) identify activated brain regions in response to stimuli presented and (iii) assess the capacity of fMRI results to predict behaviour change.

2.3. Methods

Search Strategy

The protocol of this systematic review was developed in accordance with the PRISMA-P guidelines (Moher et al., 2015). An electronic search was conducted using Medline/PubMed; Psych INFO; SPORT Discus; Web of Science (Core Collection); Cochrane Library; and Open Grey. The reference lists of included records were manually screened for identifying additional relevant records. The electronic database search was conducted on the 10th January 2017. The search strategy was identical across databases, but the affiliation field was adjusted for each database (Table 2.1). The search strategy used for all databases was: ("functional magnetic resonance imaging" OR "functional MRI" OR fMRI OR "blood oxygen level dependent" OR BOLD OR neuroimaging) AND (smoke* OR smoking OR cigarette OR tobacco OR alcohol OR drink OR "sedentary lifestyle" OR sedentary behavio* OR sedentar* OR sitting OR "physical activity" OR "physical inactivity" OR "activities of daily living" OR fitness OR exercise OR food OR snack OR diet OR eat OR eating OR calorie OR caloric OR campaign OR message OR messaging OR communication OR "mass media" OR PSA OR "public service announcement" OR graphic OR warning OR label OR image OR video).

Table 2.1. An outline of the electronic database search affiliations

Electronic database	Search criteria applied
MEDLINE/PubMed	Title and abstract
Psych INFO	Abstract only
SPORT Discuss	Abstract only
Web of Science	Title only
Cochrane Library	Title/abstract/keywords
Open Grey	No restriction applied

Selection criteria and study selection

To be included, identified records had to meet the following criteria: (i) published in English prior to January 2017; (ii) involved human participants aged ≥10 years; (iii) investigated physical activity, sedentary behaviour, dietary intake, smoking and/or alcohol consumption; (iv) assessed health messages; and (v) studied subjects using fMRI. We excluded all systematic reviews and meta-analyses. Record screening and data extraction were conducted using DistillerSR version 2.0 (Evidence Partners, Ottawa, Canada). After inspection for any duplicates, the titles and abstracts of all records were reviewed by one reviewer (MW). Where a decision to include or exclude was not attained based on the title/abstract, the full text was sourced. Full text records were examined by two reviewers (MW and MO). Conflicts were discussed and if consensus was not achieved, a third reviewer (DE) was consulted.

Recorded variables, data extraction and analysis

Data were extracted on standardised forms developed a priori by the lead author for the following variables: authors and year of publication; publication title, number of subjects included within analyses; number of subjects excluded from analyses; age; gender distribution; subject handedness; lifestyle behaviour investigated; fMRI task design; fMRI principle findings; presence of a follow up component and follow up principle findings. Further fMRI methodological variables were extracted (Appendix B and C).

2.4. Results

Full details of the search results, including reasons for exclusion are summarised in Figure 2.1. Total search results obtained from each database are presented in Table 2.2. Of 13,836 records identified by the electronic database searches, 13,420 records (97%) were excluded based on title and abstract sifting. Of the remaining 416 records, 400 (96.2%) were excluded during full-text sifting: 350 (87.5%) because they did not assess health messages, 20 (5%) due to inappropriate article type, 15 (3.8%) did not investigate fMRI and a lifestyle behaviour of interest in this review, 9 (2.3%) had no visual stimuli, 2 (0.5%) did not provide sufficient detail, 2 (0.5%) studied subjects aged <10 years and 2 (0.5%) were duplicates. Reference lists of the 16 included records yielded 2 additional records for inclusion; resulting in 18 identified studies for this review.

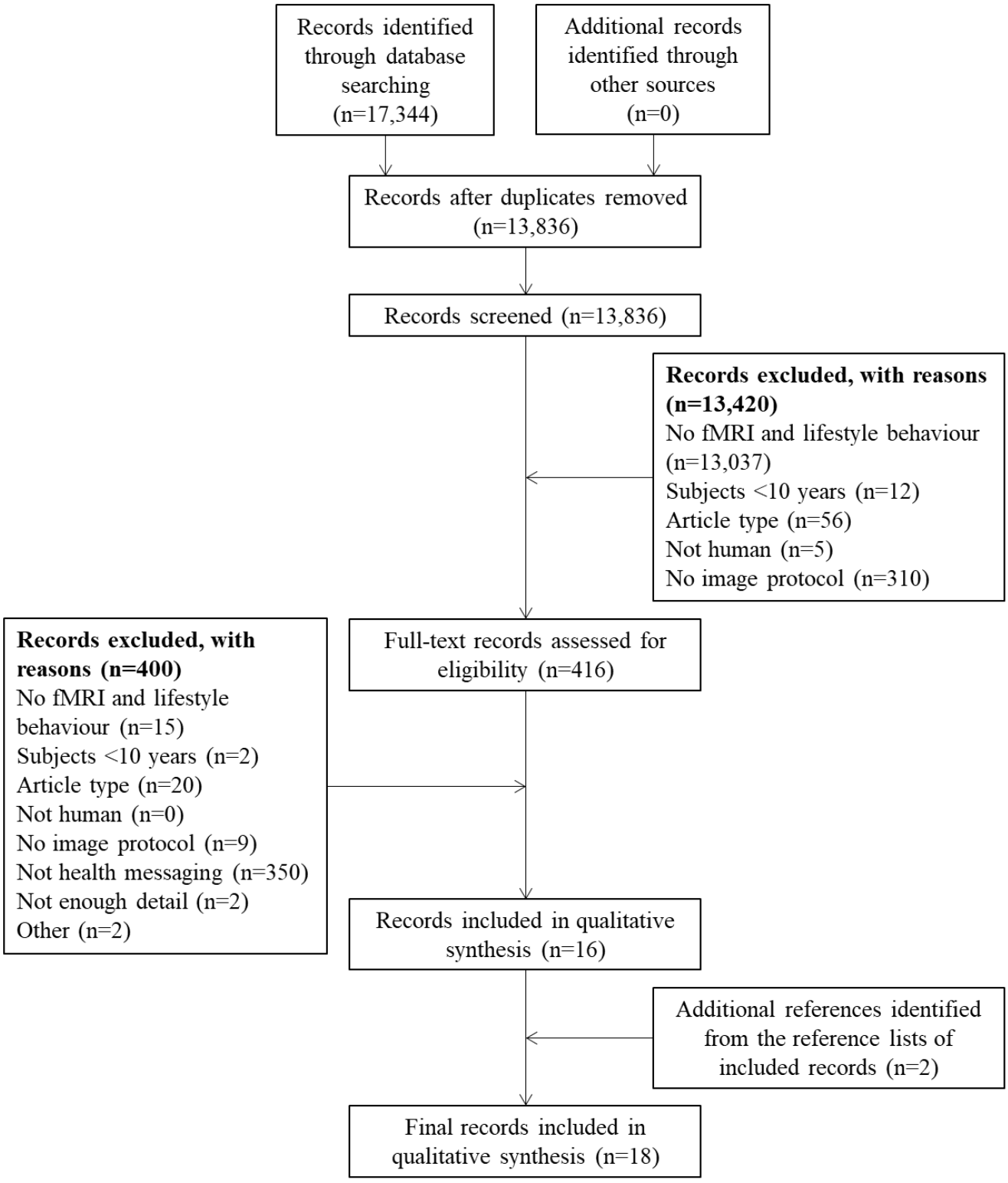

Figure 2.1. A flow diagram of how the studies were identified

Table 2.2. An outline of the search results from the electronic databases

Electronic database	Number of search results
PubMed	5,859
SPORT Discus/Psych INFO	5,342
Web of Science (Core Collaboration)	3,178
Cochrane Library	2,883
Open Grey	82
Total	17,344

Characteristics of included studies

Of the resulting 18 studies, studies investigated smoking (k=15), diet (k=2), physical activity and sedentary behaviour (k=1) and no studies were included for alcohol consumption (see Table 2.3). All studies were published between January 2009 and November 2015 (inclusive). The sample sizes of the included studies ranged from having 24 to 91 participants. Included studies recruited participants between the ages of 13 and 69 years. Fourteen (77.8%) studies recruited both males and females, 1 (5.6%) study recruited males only and 3 (16.7%) studies did not provide sufficient detail.

Of the 18 studies, ten (55.6%) were cross-sectional and eight (44.4%) were longitudinal in design. The eight longitudinal studies followed up participants one to four months following fMRI and were conducted via telephone, appointment or email to assess level of smoking abstinence (k=6), objectively measure sedentary behaviour/physical activity (k=1) or intention to quit smoking (k=1).

Fourteen (77.8%) of studies were conducted in the USA, specifically Michigan (k=6), Pennsylvania (k= 6), California (k=1) and South Carolina (k=1). The remaining studies were conducted in Germany (k=2) and Canada (k=2). Further characteristics are provided in Table 2.3.

Table 2.3. Characteristics of each of the studies included

Title	N included within analyses	N excluded from analyses	Mean age (SD)	Gender	Handed-ness	Author, year
Physical Activity or Sedentary Behaviour						
Self-affirmation alters the brain's response to health messages and subsequent behaviour change	46	21	Affirmed 33.7 (13.5); control 30.1 (13.1)	27 F 19 M	45 R	Falk et al., 2015
Diet						
Nutrition labels influence value computation of food products in the ventromedial prefrontal cortex	25	10	23.3 (4.4)	14 F 11 M	Detail not provided	Enax et al., 2015
Relation of obesity to neural activation in response to food commercials	30	Detail not provided	15.2 (1.1)	17 F 13 M	Detail not provided	Gearhardt et al., 2014
Smoking						
Neural responses to elements of a web-based smoking cessation program	41	Detail not provided	38.3 (11.5)	10 F 31 M	41 R	Chua et al., 2009
Neural correlates of message tailoring and self-relatedness in smoking cessation programming	24	Detail not provided	40 (11.2)	12 F 12 M	24 R	Chua et al., 2009
Self-related neural response to tailored smoking-cessation messages predicts quitting	91	Detail not provided	37.5 (11.5)	44 F 47 M	91 R	Chua et al., 2011

Title	N included within analyses	N excluded from analyses	Mean age (SD)	Gender	Handed-ness	Author, year
Brain activity in self- and value-related regions in response to online antismoking messages predicts behaviour change	46	4	32.1 (12.6)	19 F 27 M	46 R	Cooper et al., 2015
Where there's smoke, there's fire: the brain reactivity of chronic smokers when exposed to the negative value of smoking	30	Detail not provided	31.9 (9.4)	15 F 15 M	29 R 1 L	Dinh-Williams et al., 2014
Executive-affective connectivity in smokers viewing anti-smoking images: an fMRI study	30	Detail not provided	31.8 (9.2)	15 F 15 M	28 R 1 L 1 A	Dinh-Williams et al., 2014
FDA cigarette warning labels lower craving and elicit frontoinsular activation in adolescent smokers	79	1	Detail not provided	Detail not provided	79 R	Do & Galvan, 2015
Neural activity during health messaging predicts reductions in smoking above and beyond self-report	28	3	45 (10.1)	15 F 13 M	28 R	Falk et al., 2011
Functional brain imaging predicts public health campaign success	44	6	Detail not provided	Detail not provided	Detail not provided	Falk et al., 2016
Amygdala response to smoking-cessation messages mediates the effects of serotonin transporter gene variation on quitting.	82	Detail not provided	Quitters 36.4 (11.4); non-quitters 38.4 (12.3)	38 F 44 M	Detail not provided	Jasinska et al., 2012

Title	N included within analyses	N excluded from analyses	Mean age (SD)	Gender	Handed-ness	Author, year
Reduced prefrontal and temporal processing and recall of high 'sensation value' ads	15	3	Detail not provided	3 F 12 M	Detail not provided	Langleben et al., 2009
Neural biomarkers for assessing different types of imagery in pictorial health warning labels for cigarette packaging: a cross-sectional study	50	Detail not provided	27.6	24 F 26 M	Detail not provided	Newman-Norlund et al., 2014
Severity of dependence modulates smokers' neuronal cue reactivity and cigarette craving elicited by tobacco advertisement	43	5	Non-abstinent 31.0 (7); never-smokers 29.0 (5)	43 M	43 R	Vollstadt-Klein et al., 2011
Content matters: neuroimaging investigation of brain and behavioural impact of televised anti-tobacco public service announcements	63	8	High AS 29.0 (1.6); low AS 30.0 (1.9)	High AS 18F 15M; Low AS 14 F 16 M	Detail not provided	Wang et al., 2013
Emotional reaction facilitates the brain and behavioural impact of graphic cigarette warning labels in smokers	19	5	Detail not provided	Detail not provided	19 R	Wang et al., 2015

Abbreviations: A, ambidextrous; AS, argument strength; F, female; L, left; M, male; N, number; R, right; SD, standard deviation

Main findings

Stimuli content and modality

Identifying the content and modality of stimuli helps provide valuable insight as to what forms of health messages are being assessed using fMRI. Full details of the stimuli presented in the eighteen studies are presented in Table 2.4. Of the eighteen identified studies, nine studies used static images (k=8 smoking, k=1 diet), four studies used videos (k=3 smoking, k=1 diet) and five studies used text-based messages (k=4 smoking, k=1 physical activity/sedentary behaviour). Static messages included the presentation of images such as banner adverts (Cooper et al., 2015) and warning labels found on cigarette packaging (Do et al., 2015). Videos included food commercials (Gearhardt et al., 2014) and public service announcements highlighting the importance of smoking cessation (Langleben et al., 2009). Finally, text-based messages included the presentation of motivational messages that encouraged smoking cessation (Chua et al., 2009) or presented tailored/untailored/neutral statements (Chua et al., 2011).

Table 2.4. An outline of the fMRI protocol and main findings of the included studies

Author, year	Modality of fMRI stimuli	Content of fMRI task	Principle findings of fMRI task	Presence of a follow up	Principle findings of the follow up
Physical activity or sedentary behaviour					
Falk et al., 2015	Visual	Promote activity and emphasise risks due to being sedentary (n=10); reasons not to be sedentary (n=10) or more active (n=10); tips for how to become more active (n=10) or less sedentary (n=10).	Affirmed participants showed greater activity within vmPFC during exposure to targeted health messages.	Accelerometry 1 month. 2 SMS messages per day: 1 value affirmation (either affirmation or control allocation) and 1 health message.	Activity within the vmPFC predicted sedentary behaviour in the subsequent month.
Diet					
Enax et al., 2015	Visual	Healthy TL (n=25); unhealthy TL (n=25); healthy GDA (n=25); unhealthy GDA (n=25)	Unhealthy TL showed significantly increased activation in the left inf. front. gyrus/dlPFC.	No follow up	N/A
Gearhardt et al., 2014	Visual (presence of audio unknown)	Food commercials (n=20); non-food commercials (n=20)	Food commercials exhibited greater activation in bilateral post. cerebellar lobe (declive), bil. middle occipital gyrus, right precentral gyrus, right inf. temporal gyrus, bil. inf. parietal lobe, left postcentral gyrus, right precuneus and right sup. parietal lobe.	No follow up	N/A

Author, year	Modality of fMRI stimuli	Content of fMRI task	Principle findings of fMRI task	Presence of a follow up	Principle findings of the follow up
Smoking					
Chua et al., 2009	Visual (presence of audio unknown)	Personalisation/feedback; motivational; instructional; control messages (targeted and neutral)	Personalisation/feedback messages activated the mPFC and precuneus/post. cingulate.	Web-based tailored smoking-cessation program and a 10-week course of nicotine patches. Follow up at 4 months	Detail not provided
Chua et al., 2009	Audio-visual	High tailored messages; low tailored messages; generic statements	High-tailored messages produced greater activity in rmPFC and precuneus/post. cingulate regions.	No follow up	N/A
Chua et al., 2011	Audio-visual	Tailored messages (n=50); untailored messages (n=50); neutral messages (n=50).	The dmPFC, precuneus, and angular gyrus were preferentially engaged by tailored messages.	Web-based tailored smoking-cessation program. Follow up at 4 months.	Greater activation in the dmPFC during tailored messages significantly predicted the odds of quitting smoking. Greater activation in the precuneus was marginally correlated.
Cooper et al., 2015	Visual	Banner ads (n=23)	Detail not provided	Follow up at 40 days.	Behaviour change was significantly related to activity in self- and value-related sub-regions of the mPFC (replicated previous findings).

Author, year	Modality of fMRI stimuli	Content of fMRI task	Principle findings of fMRI task	Presence of a follow up	Principle findings of the follow up

Dinh-Williams et al., 2014	Visual	Aversive smoking-related (n=25);
		aversive non-smoking related (n=25);
		appetitive smoking-related (n=25);
		neutral (n=25).
			Aversive smoking-related elicited activations in the visual association cortex and ext. visual system, the temporal and parietal lobes, limbic system, lat. orbitofrontal cortex, inf. front. gyrus and mPFC.	No follow up	N/A

Dinh-Williams et al., 2014	Visual	Aversive smoking-related (n=25); aversive IAPS control (n=25); neutral IAPS control (n=25)	Aversive smoking-related elicited significantly greater activations in regions of the occipital, temporal and parietal lobes, amygdala, lat. orbitofrontal cortex, inf. front. gyrus and mPFC.	No follow up	N/A
Do et al., 2015	Visual	FDA warning labels (n=9); non-graphic labels (control) (n=9)	Smokers' demonstrated blunted recruitment of insula and dlPFC relative to non-smokers.	No follow up	N/A

Author, year	Modality of fMRI stimuli	Content of fMRI task	Principle findings of fMRI task	Presence of a follow up	Principle findings of the follow up
Falk et al., 2011	Visual (presence of audio unknown)	TV commercials relevant to smokers who were trying to quit (n=16).	Detail not provided	Follow up at 1 month.	Neural activity in the mPFC significantly predicted behaviour change. The med. precuneus/post. cingulate and a region involved in motor planning supplementary motor area were also highly associated.
Falk et al., 2016	Visual	Anti-smoking images with a tag-line Negative images (n=10) Neutral images (n=10) Personal/control images (n=10)	Detail not provided	Population-level email campaign (n=400,000). Presented either anti-smoking or neutral image with a tagline to stop smoking. Measured intention to quit via option to obtain free nicotine patches	Activity within mPFC sub-region predicted population-level campaign responses Self-related neural processing predicted outcomes in response to graphic warning labels, but not in response to compositionally similar neutral images.
Jasinska et al., 2012	Audio-visual	Tailored messages (n=50); untailored messages (n=50); neutral messages (n=50).	Detail not provided	Web-based tailored smoking-cessation program and a 10-week course of nicotine patches. Follow up at 4 months.	The mean amygdala response was a significant predictor of subsequent post-intervention quitting outcome.

Author, year	Modality of fMRI stimuli	Content of fMRI task	Principle findings of fMRI task	Presence of a follow up	Principle findings of the follow up
Langleben et al., 2009	Audio-visual	Anti-smoking PSAs (n=8); neutral videos (n=8)	PSAs were associated with higher activity in the inf. and mPFC, the occipital cortex (fusiform and lingual gyri) and the temporal cortex (hippocampus and parahippocampus).	No follow up	N/A
Newman-Norlund et al., 2014	Visual	Graphic health warning label (n=19); suffering health warning label (n=19); symbolic health warning label (n=19)	Stimuli elicited a significant neural response in the amygdala, insula and visual association cortex, front. gyrus, temporal gyrus, parietal lobe (inf.), suppl. motor area, parahippocampal gyrus and thalamus.	No follow up	N/A
Vollstadt-Klein et al., 2011	Visual	Smoking-related (n=45); control (n=45)	Moderately dependent smokers' brain activity elicited by tobacco advertisement was higher in the amygdala, hippocampus, putamen and thalamus.	No follow up	N/A

Author, year	Modality of fMRI stimuli	Content of fMRI task	Principle findings of fMRI task	Presence of a follow up	Principle findings of the follow up
Wang et al., 2013	Audio-visual	Anti-smoking PSAs High AS/high MSV (n=8); high AS/low MSV (n=8); low AS/high MSV (n=8); low AS/low MSV (n=8)	The interaction of AS and MSV was observed in the bil. inf. parietal lobule, left inf. front. gyrus, left fusiform gyrus, the right dmPFC, and the precuneus.	Follow up at 1 month.	Activation in the dmPFC predicted the urine cotinine levels.
Wang et al., 2015	Visual	High FDA graphic warning label (n=12); low FDA graphic warning label (n=12); control (n=12)	Graphic warning labels evoked greater activation in the bil. occipitoparietal cortex, including visual and fusiform areas, cuneus and precuneus, bil. temporal and inf. front. cortices, amygdala, hippocampus and parahippocampus.	No follow up	N/A

Abbreviations: AS, argument strength; bil., bilateral; dmPFC dorsomedial prefrontal cortex; FDA, Food and Drug Administration; ext., extended; front., frontal; GDA, guideline daily amount; IAPS, International Affective Picture System inf., inferior; lat., lateral; med., medial; mPFC, medial prefrontal cortex; mid., middle; MSV, message sensation value; post., posterior; PSAs, public service announcements; rmPFC, rostral medial prefrontal cortex; sup., superior; suppl., supplementary; TL, traffic light; vmPFC ventromedial prefrontal cortex

Brain activations

The most common brain regions activated in the studies are presented in Table 2.5.

Static health messages

Significantly more activation in the temporal and parietal lobes, lateral orbitofrontal cortex, inferior frontal gyrus and medial prefrontal cortex were consistently observed across two studies assessing aversive smoking versus control images (Dinh-Williams et al., 2014; Dinh-Williams et al., 2014). Another study observed activations in other regions (e.g. amygdala and hippocampus) in response to tobacco advertisement images (Vollstadt-Klein et al., 2011). Of the three studies investigating graphic warning labels, two studies identified significant neural responses in the amygdala (Newman-Norlund et al., 2014; Wang et al., 2015). The two remaining smoking-related studies (Cooper et al., 2015; Falk et al., 2016) focused on the predictive capacity of neural activation therefore the results are not highlighted in this section. Only one study (Enax et al., 2015) examined neural activation toward static health messages restricting the opportunity for comparison. No studies were identified for physical activity or sedentary behaviour.

Video health messages

Of the three studies investigating smoking-related health messages presented by video, one study (Falk et al., 2016) focused only on the predictive capacity of brain activation on subsequent behaviour. The other two studies examined neural activation in response to anti-smoking public service announcements but compared these stimuli with neutral videos (Langleben et al., 2009) or varying videos with varying levels of 'message sensation value' and 'argument strength' (Wang et al., 2013). This was reflected in the findings which highlighted no common brain regions between them. In addition, only one study (Gearhardt et al., 2014) investigated diet health messages delivered by video. No studies were identified for physical activity or sedentary behaviour.

Text-based health messages

Three of the four studies identified regions within the prefrontal cortex and precuneus as preferentially engaged in response to tailored/personalised text-based messages. These regions included the rostral medial prefrontal cortex (Chua et al., 2009), medial prefrontal cortex (Chua et al., 2009) and the dorso-medial prefrontal cortex (Chua et al., 2011). The fourth study instead focused on the predictive capacity of brain activation on subsequent behaviour (Jasinska et al., 2012). In contrast, only one study (Falk et al., 2015) investigated this form of

health message for physical activity/sedentary behaviour. No studies were identified for text-based health messages relating to diet.

Table 2.5. An outline of how often activated brain regions were reported within the identified studies (criteria: ≥2 studies reported the brain region)

	PA/ SB	**Diet**		**Smoking**										
	Falk et al., 2015	Enax et al., 2015	Gearhardt et al., 2014	Chua et al., 2009	Chua et al., 2009	Chua et al., 2011	Dinh-Williams et al., 2014	Dinh-Williams et al., 2014	Do et al., 2015	Langleben et al., 2009	Newman-Norlund et al., 2014	Vollstadt-Klein et al., 2011	Wang et al., 2013	Wang et al., 2015
Inferior frontal gyrus		✓	✓				✓	✓			✓	✓	✓	✓
Precuneus	✓		✓	✓	✓	✓				✓			✓	✓
Amygdala							✓	✓	✓		✓			✓
Fusiform							✓				✓	✓	✓	✓
Inferior parietal lobe			✓				✓					✓	✓	
Middle temporal gyrus	✓						✓				✓			✓
Precentral gyrus			✓								✓	✓		✓
Lingual gyrus										✓	✓			✓
Medial prefrontal cortex				✓	✓			✓						
Middle frontal gyrus										✓	✓	✓		
Parra-hippocampal gyrus										✓	✓			✓
Posterior cingulate	✓			✓	✓									
Superior frontal gyrus	✓						✓					✓		
Caudate									✓	✓				

	PA/ SB	**Diet**		**Smoking**										
	Falk et al., 2015	Enax et al., 2015	Gearhardt et al., 2014	Chua et al., 2009	Chua et al., 2009	Chua et al., 2011	Dinh-Williams et al., 2014	Dinh-Williams et al., 2014	Do et al., 2015	Langleben et al., 2009	Newman-Norlund et al., 2014	Vollstadt-Klein et al., 2011	Wang et al., 2013	Wang et al., 2015
Cerebellum										✓				✓
Dorsolateral prefrontal cortex		✓							✓					
Dorsomedial prefrontal cortex						✓							✓	
Hippocampus											✓			✓
Inferior occipital							✓							✓
Insula									✓		✓			
Middle occipital gyrus			✓				✓							
Putamen									✓					✓
Superior temporal gyrus												✓		✓

Abbreviations: PA, physical activity; SB, sedentary behaviour.

Predictive capacity of fMRI for behaviour change

In total, eight studies assessed the predictive capacity of fMRI (k=7 smoking, k=1 physical activity/sedentary behaviour). Of the seven studies focused on smoking, six studies identified that the following activated brain regions were predictive of smoking abstinence: the dorsomedial prefrontal cortex (k=2), medial prefrontal cortex (k=2), amygdala (k=1) and the supplementary motor area (k=1). The physical activity/sedentary behaviour study (Falk et al., 2015) identified the ventromedial prefrontal cortex as predictive of subsequent time spent sedentary.

2.5. Discussion

Summary

The present review identified 18 studies; 15 relating to health messages about smoking, two relating to health messages about diet and one on health messages about physical activity/sedentary behaviour. Areas of the prefrontal cortex and amygdala were most commonly activated with increased activation of the ventromedial prefrontal cortex predicting subsequent behaviour change (e.g. smoking cessation). Most of the evidence on the utility of fMRI to facilitate behaviour change currently relates to smoking and there was a lack of RCTs; limiting findings to correlations rather than causal interpretation. More fMRI studies on health messages relating to physical activity, sedentary behaviour, dietary intake and alcohol consumption are needed that incorporate an RCT design.

Stimuli content and modality

The present review highlighted that a range of anti-smoking materials were investigating both pictorial and video stimuli such as US Food and Drug Administration (FDA) warning labels (Do & Galvan, 2015; Wang et al., 2015) and public services announcements (PSAs) (Langleben et al., 2009), respectively. Studies that compared neural responses to tailored and untailored messages observed activations in the dorsomedial prefrontal cortex and precuneus/posterior cingulate (e.g. Chua et al., 2009, 2011). Other studies demonstrated that aversive smoking stimuli, compared with neutral images, elicited greater activations in the amygdala (Dinh-Williams et al., 2014); often associated with emotion regulation (LeDoux, 2003). With a range of anti-smoking materials currently advertised, it must be acknowledged that people respond and engage differently with them. For instance, Dos and Galvan identified that current smokers had a blunted response in the dorsolateral prefrontal cortex and insula

relative to non-smokers to cigarette warning labels (Do et al., 2015). This suggests that the health messages were not causing the same neural response in the smokers as in the non-smokers and so perhaps multiple versions of health messages should be produced to target all people. For example, specific messaging materials could be developed to highlight the benefits of not starting a behaviour (proactive approach) and other materials to highlight the benefits of stopping a behaviour (reactive approach). Presenting pictures of people living with obesity, having limited mobility or other health issues such as diabetic foot on chairs and inside escalators (including sites that are likely to attract active individuals e.g. gyms and parks) could be a comparable approach to promote physical activity, within the community, across the entire population (i.e. active and inactive).

As demonstrated in the present review, point-of-decision prompts such as pictures on cigarette packaging or traffic light coding systems found on food items are widely used in anti-tobacco and food industry communications, respectively, to deter purchasing. Other methods, such as billboard advertisements and videos (e.g. PSAs) enable similar but wider messages to reach the wider public and are often accompanied by graphic health messages; suggested to elicit stronger emotional responses than text-based messages alone (Kees et al., 2006). As previously mentioned, for physical activity and sedentary behaviour, point-of-decision prompts are placed at specific locations where people are forced to make a behavioural decision as to whether be active or sedentary, respectively. For instance, prompts that encourage people to take the stairs rather than the escalator have shown short-term promise (Webb & Eves, 2005). However, it is currently unknown whether these highlighted health messages activate brain regions associated with 'the self'; previously suggested to motivate people to adjust behaviour (Wheeler et al., 2007). Efforts to change behaviour generally result in short-term successes and a subsequent relapse or complete failure (Polivy & Herman, 2002). These failures are often aligned to the difficulty experienced when changing a habit and so rely on the use of cues and triggers to support the habit formation process (Neal et al., 2012). Therefore, more research using fMRI needs to be conducted to focus on alternative point-of-decision prompts that relate to promoting physical activity, minimising sedentary behaviour and improving dietary intake. Overall, this will likely inform the distribution of effective health messages across the different lifestyle behaviours in various locations to encourage positive behaviours.

Activated brain regions

The present review identified that the ventromedial prefrontal cortex, medial prefrontal cortex, and dorsomedial prefrontal cortex were activated in response to anti-smoking health messages

that were aversive or tailored. No studies explicitly stated whether the tailored messages were aversive or not. The medial prefrontal cortex is a well-established area of the brain associated with self-related processing (Lieberman, 2010); suggesting that individuals are self-reflecting whilst shown stimuli and are therefore potentially more likely to be engaging with the stimulus compared with an individual who does not have activation in that region. However, as with all fMRI research, caution is advised when interpreting findings; mainly attributed to the notion of reverse inference which suggests that brain activation infers the engagement of a specific cognitive process (Poldrack, 2006). Tailored health messages activated regions of the prefrontal cortex, precuneus and posterior cingulate regions which are associated with retrieving episodic autobiographical memories (Levine et al., 2004) as well as reflecting on one's own traits (Johnson et al., 2002) and personal intentions (Den Ouden et al., 2005). The present review identified nine additional studies to those highlighted in a recent neuroimaging review (Kaye et al., 2016) which focused on wider health communication; including studies focusing on narcotic substance use, safe sex and sun safety. These studies investigated the perceived value of health messages and how greater neural activity was observed in certain populations (e.g. high risk cannabis users) (Kaye et al., 2016).

Presenting caloric information activated the inferior frontal gyrus/dorsolateral prefrontal cortex region (Enax et al., 2015); a region implicated in self-control (Hare et al., 2011). The importance of this brain region is implicated in various domains of self-control, including compliance toward social norms (Maldjian et al., 2003) and controlling impulses in inter-temporal choice (Figner et al., 2010). The ventromedial prefrontal cortex is implicated in simple-choice value computation (Enax et al., 2015). These findings suggest that health messages resonate with the individual and encourage them to self-reflect but it does not confirm that those individuals subsequently change their behaviour following exposure to the health message. Other studies, not eligible to be included in the present review, have begun to examine neural responses to pictures of individuals being physically active or sedentary (Jackson et al., 2014; Kullmann et al., 2014). For instance, if an individual viewed a picture of someone else jogging, what brain regions are activated and does exposure result in desired changes to physical activity? Recent advances, such as the release of a new parcellation (mapping) tool identifying 97 further sub-regions within the cerebral cortex (Glasser et al., 2015), will help to further elucidate knowledge around the specific functions aligned with regions of interest which will help confirm findings obtained via studies using fMRI.

Predictive capacity of fMRI for behaviour change

The present review identified that the brain regions that were identified as predictive (by association) of smoking cessation were the dorsomedial prefrontal cortex, amygdala, the supplementary motor area and the medial prefrontal cortex; associated with self-related processing (Lieberman, 2010). The other lifestyle behaviour study that conducted a follow up focused on changes in physical activity and sedentary behaviour. Interestingly, Falk and colleagues identified a different brain region as predictive of subsequent reductions in time spent sitting with activations observed in the ventromedial prefrontal cortex (Falk et al., 2015). Unfortunately, findings from the present review confirm that all studies that investigated the predictive capacity of fMRI for behaviour change conducted prospective, longitudinal studies and so report correlational data which cannot be causal. In addition, there appeared to be inconsistent findings such that there was not a single brain region that was activated across all of the health message stimuli due to the variety of health messages presented.

Falk and colleagues also assessed the role of self-affirmation; in particular, how exposing individuals to their core values (e.g. friends and family, money and religion) prior to the task demonstrated that the stimuli was more self-relevant and valuable (Falk et al., 2011). The link between neural activity and behaviour change via self-processing is supported (Falk et al., 2010) with findings suggesting that individuals more engrossed in anti-smoking advertisements report an increased benefit (i.e. are less likely to smoke or more likely to stop smoking) (Dunlop et al., 2008) and that self-relevant messages are likely more effective than generic messages (Dietz et al., 2008; Strecher et al., 2008). Findings from Kaye and colleagues confirmed that activation in the medial prefrontal cortex accounted for additional variance beyond that of self-report measures (Kaye et al., 2016). Unfortunately, as highlighted by the present review, there is currently limited or a lack of evidence for changes in physical activity, sedentary behaviour, diet and alcohol following health message exposure. Future studies should consider implementing an RCT within their longitudinal studies to promote research assessing behaviour change across the different lifestyle behaviours.

Future considerations

With an increase in the application of digital technologies within healthcare systems for use in patients with chronic conditions, it is an important time to ensure that the health messages provided by these devices are effective (Driver, 2016). Presenting health messages via digital platforms such as wearable devices to promote standing and walking or via smartphone apps

to help monitor food, cigarette and alcohol consumption, given their omnipresence, could be very effective and not too dissimilar to the handheld health message platform of cigarettes or food packaging. That said, it must also be acknowledged that equivalent images (e.g. of yellow teeth for smoking) to reflect the physiological consequence of physical inactivity and sedentary behaviour are not as direct. These images could include foot amputations and atherosclerosis, as a couple of examples, but sadly these images could also be aligned to poor dietary intake; restricting our ability to capture peoples responses to their movement behaviours. Overall, future fMRI studies should aim to evaluate brain responses to different forms of health messages across the different lifestyle behaviours and incorporate longitudinal but controlled study designs to optimise the interpretation and consistency of study findings.

Literature Methodology

Of the 13 (72.2%) studies that stated their recruitment strategy, the majority presented advertisements in the community or via the internet; thus, recruiting self-selected and non-randomised individuals. In addition, only two studies recruited adolescents despite the onset of an unhealthy lifestyle often beginning in the early-to-mid adolescent years. Most studies were conducted in either Michigan or Pennsylvania in the USA (k= 16); potentially attributable to the general limitations of fMRI such as restricted access and cost. In addition, nine studies either failed to report participant handedness or recruited a mixture of left, right and ambidextrous handed participants. The importance of reporting handedness is due to its clear link to cerebral dominance for activities such as language processing (Goodglass & Quadfasel, 1954). Future research would benefit from standardising, and precisely measuring, the time between tobacco, food and alcohol consumption and exercise before the onset of the fMRI task.

Limitations

The present review acknowledges the following limitations. Firstly, there were only 18 studies identified by the electronic database search and reference lists and there was a lack of causational studies; therefore, it is difficult to draw any conclusions. Secondly, only eight studies examined behaviour change with seven (87.5%) of these conducted in relation to smoking cessation. In addition, there was a lack of studies identified for physical activity, sedentary behaviour, diet and alcohol. Studies published outside of the databases searched were not considered for inclusion. Future research is required to examine the utility of fMRI to examine health messaging relating to these lifestyle behaviours.

2.6. Conclusions

This review highlights a skewed focus on the impact of health messages on brain activation relating to smoking behaviours and reveals gaps that need addressing in the physical activity messaging literature. Collating findings from multiple lifestyle behaviours could prove useful to begin producing more persuasive messages for population behaviour change; however, there is currently a deficiency of studies across the lifestyle behaviours to investigate this at this stage. Regardless of this, the review highlights that the prefrontal cortex and amygdala were most commonly activated in response to health messages and that the ventromedial prefrontal cortex was predictive (by association) of subsequent behaviour change. Future studies should focus on the assessment of point-of-decision prompts, PSAs and tailored messages (e.g. feedback notifications) across all lifestyle behaviours. Considering these findings, we are going to explore the use of fMRI to monitor brain activation in response to stimuli relating to personalised feedback often presented on digital health technologies.

Chapter Three

Study Two:

Brain activation in response to personalised behavioural and physiological feedback from self-monitoring technology: Pilot Study

Whelan, ME; Morgan, PS; Sherar, LB; Kingsnorth, AP; Magistro, D; Esliger, DW. Brain activation in response to personalised behavioural and physiological feedback from self-monitoring technology. *Journal of Medical Internet Research*. 2017;19(11): e384.

Appendix D. Original publication has been adapted to fit within this thesis.

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3.1. Introduction

Physical inactivity, insufficient levels of physical activity, is attributable to 9% of premature mortality and 7% of type 2 diabetes cases (Lee et al., 2012). In addition, sedentary behaviour, defined as 'any waking behaviour characterised by an energy expenditure ≤1.5 metabolic equivalents of task (METs) while in a sitting or reclining posture' (Tremblay et al., 2017), has been strongly associated with poor cardiometabolic health (Henson et al., 2013). With adults spending an estimated 7 hours sedentary each day (Matthews et al., 2008) and the prevalence of type 2 diabetes expected to rise to 592 million by 2035 (Guariguata et al., 2014), it is critical to address the prevalence of physical inactivity and time spent sedentary for the prevention of type 2 diabetes and other important chronic, noncommunicable diseases.

Over the last decade, wearable activity monitors have grown in popularity in consumer markets to help users track their movement behaviours (e.g. active minutes, step counts, distance travelled, time spent sitting) (Loveday et al., 2015; Sanders et al., 2016). Over the same period, wearable physiological sensing devices (e.g. heart rate monitors, continuous glucose monitors) have been evolving and are now venturing beyond the clinical domain into consumer-focused markets (Bonander & Gates, 2010). The allure of these wearable technologies is that they provide users with real-time, personalised health feedback that may encourage positive lifestyle behaviours (e.g. moving more, sitting less, eating more healthily) (Piwek et al., 2016). However, with 32% of individuals failing to continue using these devices beyond 6 months following purchase (Ledger et al., 2014), there is a need to optimise the feedback provided to the users to maintain adoption and sustain engagement with the information presented. Patel and colleagues suggest that providing explanatory feedback in an understandable manner is important to encourage sustained use (Patel et al., 2015). Given that sustained behaviour change is often poorly reported and not often achieved (Fjeldsoe et al., 2011), assessing how people respond to this feedback at a cortical level (by monitoring changes in brain activation) could reveal additional insight above traditional qualitative tools such as focus groups or interviews.

Neuroimaging techniques are useful to recognise and identify the intricate relationships between cognitions, brain functions and behaviour (Lee & Harris, 2015). There has been growing interest in the community toward communication neuroscience, research that provides a deep understanding of attitude and behaviour change (Falk et al., 2010). Moreover, communication neuroscience research suggests that people's intentions and behaviour are largely affected by the content and format of an advertisement (Fishbein & Cappella, 2006).

One key neuroimaging tool is functional magnetic resonance imaging (fMRI), which monitors neural responses as information is presented (Lieberman, 2010) (e.g. health messages and advertisements (Chua et al., 2011; Falk et al., 2010, 2011). Receiving personalised (or self-related) feedback is often associated with activation within the rostral medial prefrontal cortex (mPFC), associated with decision making and mimicry behaviour (Euston et al., 2012; Wang & Hamilton, 2014), and the precuneus/posterior cingulate region, often associated with personal reflection (Johnson et al., 2002; Kelley et al., 2002; Phan et al., 2004). In particular, self-relevant messages elucidate more activation within the mPFC than untailored messages (Chua et al., 2009) and can predict behaviour change (Fishbein et al., 2000). Meta-analyses of fMRI studies also suggest that the mPFC and precuneus/posterior cingulate regions mediate self-related processing (Northoff et al., 2006).

Functional MRI can improve our understanding of how cognitive processes vary between those who do change their behaviour following exposure to a stimulus and those who do not (Cascio et al., 2013). The mPFC is positioned whereby activation in this region can predict individual behaviour change (Cooper et al., 2015; Falk et al., 2010, 2011). To date, research has largely focused on identifying neural responses to antismoking material (Cooper et al., 2015; Dinh-Williams et al., 2014; Falk et al., 2011) rather than diet, alcohol consumption, physical inactivity, or sedentary behaviour (Whelan et al., 2017; Chapter Two). Investigating how people respond to personalised feedback relating to these lifestyle behaviours could offer crucial insight into how best to disseminate feedback to maximise effect; potentially helping to design materials that optimise population health (Vecchiato et al., 2011). For instance, observed reductions in smoking rates have been attributed to a number of influences, in part, by the dissemination of health message labels on cigarette packaging (Wakefield et al., 2008). Given that literature to date has largely assessed how people respond to antismoking materials, fMRI may help identify how people's brains respond to information commonly presented on the screens of wearable devices and associated smartphone apps. We hypothesize that the mPFC and precuneus/posterior cingulate regions will be activated given the presentation of personalised (self-relevant) feedback (Johnson et al., 2002; Kelley et al., 2002; Northoff et al., 2006; Northoff & Bermpohl, 2004; Phan et al., 2004).

3.2. Aims and objectives

The aims of this study were to (i) identify regions of the brain activated in response to personalised behavioural and physiological feedback messages and (ii) examine behaviour change and associations with levels of brain activation.

3.3. Methods

Participants

A total of 33 participants were recruited from a university in the UK via advertisement posters and email. Participants were aged 30 to 60 years, had no mobility-related musculoskeletal problems, had no confirmed diagnosis of diabetes, were willing and able to comply with the study protocol, met standard fMRI safety criteria (no metal in body, not claustrophobic, not pregnant), and were right-handed (self-reported). All participants completed a physical activity readiness questionnaire (Warburton et al., 2011) prior to participation with positive responses assessed by a clinician.

Experimental procedures were approved by the Loughborough University Ethics Advisory Committee (R15-P142).

Procedure

Data were collected between June and September 2016. The study design is presented in Figure 3.1. During the first appointment, participants provided informed consent; answered questions relating to age, sex, ethnicity, and education; and completed a selection of health measures (body composition, blood pressure, and blood sample). Following the identification of a gap within the fMRI literature (Chapter Two), physical activity and sedentary behaviour health messages were partly employed alongside glucose feedback, as the stimulus for Study Two. As a result, participants were fitted with three devices to monitor their physical activity, sedentary behaviour, and glucose levels for 14 days. In addition, participants were provided an education booklet to take away with them prior to baseline to read approximately one week before their fMRI appointment (Appendix E). This booklet included definitions and UK national recommendations (e.g. 150 minutes of moderate-to-vigorous physical activity per week and target glucose range) to help minimise any variations in knowledge. The fMRI took place at the second appointment (on average 32.4±10.5 days following the first appointment); following this, participants continued to wear two devices to monitor physical activity and sedentary behaviour for 8 days. Participants were not informed about the true reason why they were wearing the devices again (i.e. to monitor behaviour change), only to monitor their behaviour once final time. At the end of the follow-up period, participants returned the devices and received a comprehensive personalised health report.

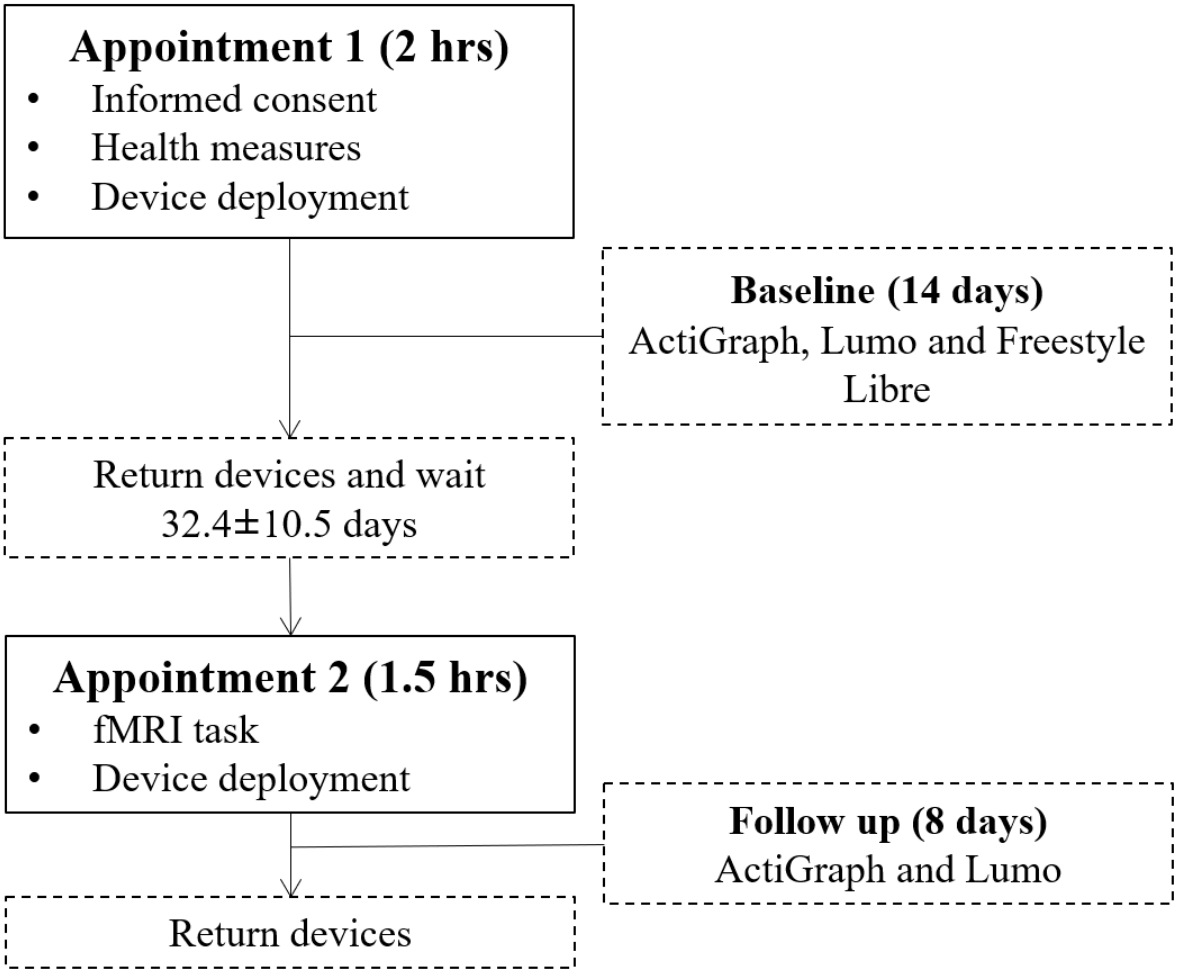

Figure 3.1. An illustration of the study design

Measures

Physical health

Weight and body fat percentage were measured using the MC 780 MA scale (Tanita) following the removal of shoes and socks. Body mass index was calculated as weight (kg) divided by height (m) squared (weight/height^2). Glucose and haemoglobin A_{1c} (HbA_{1c}) were analysed using a Cholestech LDX system and Afinion AS100 Analyzer (both Alere Inc), respectively. Participants arrived fasted for ≥8 hours prior to the collection of a capillary blood sample.

Accelerometry

A wGT3X-BT accelerometer (ActiGraph, Pensacola, FL) (Figure 3.2) was worn on a waistband (on the right anterior axillary line) to objectively measure physical activity. Participants were asked to wear the validated device (Aadland & Ylvisåker, 2015) during waking hours and to remove for any water-based activities (e.g. showers or bathing). The

accelerometry data were collected at 100 Hz resolution and integrated into 60 second epochs using ActiLife version 6.13.2 (ActiGraph LLC) and processed using Kinesoft version 3.3.80 (Kinesoft). Data were classified as stationary time (≤100 counts per min [cpm]), light activity (101 to 2019 cpm), or MVPA (>2019 cpm) (Troiano et al., 2008). Nonwear was identified by an interval of at least 60 consecutive minutes of zero activity intensity counts, with allowance for up to 2 minutes (Troiano et al., 2008). Participants who had <4 valid days were excluded from analyses. A valid day was defined as having ≥10 hours of monitor wear. Accelerometers were initialised to begin monitoring at the end of appointments, which meant participants had a variable amount of possible wear on the first day. As a result, to standardise the opportunity for participants to adhere to device wear, days 2 through 8 were analysed for both baseline and follow-up. A global wear time variable was calculated as the mean of wear time at baseline and follow-up.

Figure 3.2. Images of the ActiGraph (left), Lumo (middle) and Freestyle Libre (right)

Inclinometry

A Lumo (Lumo Bodytech Inc, Palo Alto, CA; Figure 3.2) posture sensor was worn on a waistband (in the lumbosacral region) in contact with the skin to measure sedentary behaviour (time spent sitting, driving, lying, standing, stepping, and number of sit-to-stand transitions) during baseline and follow-up. Devices were calibrated to the wearer using the Lumo app which offers a default calibration process and was used as a way to check it was detecting various postures. Participants were asked to walk for 30 seconds before doing at least two sit-to-stand transitions. Whilst doing this, the researcher checked the app's avatar was replicating the participant's movements. Participants were asked to wear the device only during waking hours, remove it for any water-based activities (e.g. showers or bathing), and place the device on charge overnight each day. The Lumo has been found to produce valid measurements of sedentary behaviour, with a mean absolute percent error of 9.5% for time spent sedentary compared with the ActivPAL (PAL Technologies Ltd) (Rosenberger et al., 2016). Data from

the Lumo devices were analysed in 5-minute epochs (highest resolution) using Excel (Microsoft Corp). Nonwear was defined by 1 of 2 criteria: (1) device removal for sleep which was automatically detected if the device was placed on charge or (2) prolonged periods of the same posture deemed to be biologically unlikely (i.e. ≥60 minutes in the position 'sit bad forward'). Prior to follow up device deployment, participants were asked to wear the devices (i.e. no emphasise was made about them having been exposed to their feedback). Again, the Lumos were set up to begin monitoring at the end of appointments and days 2 through 8 were analysed for both baseline and follow-up.

Flash glucose monitoring

The Freestyle Libre flash glucose monitor (Abbott Diabetes Care, Alameda, CA, Figure 3.2) measures interstitial glucose levels via a minimally invasive 5 mm flexible filament inserted into the posterior upper arm. The sensor works based on the glucose-oxidase process by measuring an electrical current proportional to the concentration of glucose. Tegaderm transparent film dressing (3M Health Care) was applied on top of the sensor to maintain its position. Participants were informed not to remove the sensor and to scan at least once every 7 hours (a conservative decision as the manufacturer states 8 hours to avoid data loss). As a result, participants were able to see their real-time glucose levels during baseline wear. An indication of how many times participants viewed this information (level of exposure) was identified by the frequency with which they scanned. Missing data were obtained because of a fault (sensor last <14 days) or the participant failed to scan at least once every 8 hours. The Freestyle Libre has been previously validated against venous sampling with an overall mean absolute difference of 11.4% with consistent accuracy throughout the 14 days (Bailey et al., 2015). Glucose data were downloaded in 15-minute epochs (highest resolution possible) using Freestyle Libre version 1.0. The raw data were used to calculate the number of high glucose events (defined as ≥8.8 mmol/L) and to identify valid days. Days were defined as valid if they met the prespecified threshold of ≥90% of data points (96 expected based on 4 readings each hour across each 24-hour period). All 14 days were analysed from baseline wear. Area under the curve was calculated from the mean area of the positive peaks across the valid days using Graph Pad Prism version 7.0.0 (GraphPad Software) and participants' fasting glucose level were used as the baseline.

Functional MRI stimuli

Twenty personalised feedback messages were created for the purposes of this study and covered 4 topics: MVPA, light physical activity, sedentary behaviour, and glucose levels (all presented in Figure 3.3 with example data). They intended to reflect feedback metrics presented on wearable technologies, but it was challenging to identify what specific metrics were included that would be meaningful to participants. Data obtained via accelerometry, inclinometry, and flash glucose monitoring were analysed and then incorporated into the feedback messages. Therefore, the values presented on the messages were personalised so that the numbers varied between participants, but the image and text remained consistent. The images were matched in visual complexity, colour, and text font using Axure RP Pro version 7.0.0.3190 (Axure Software Solutions Inc) to standardise stimuli across participants. Picture icons were identified and downloaded from an icon resource website (www.flaticon.com).

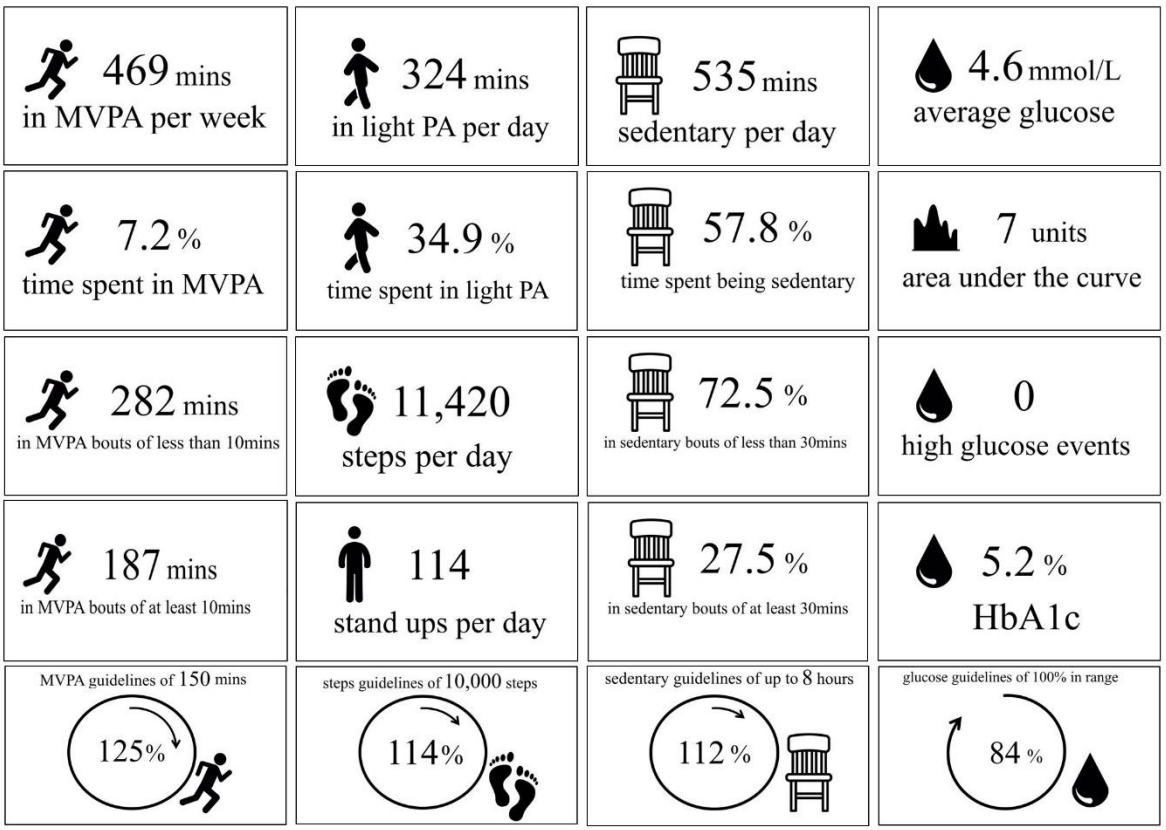

Figure 3.3. An example of the personalised feedback stimuli images displayed to participants inside the MRI scanner

Stimuli were presented on a monitor located 2.8 m behind the centre of the scanner bore and viewed by a mirror mounted on the head coil. Adjustments to the positioning of the mirror were made for participants to ensure that the full monitor screen could be seen. We examined neural

activity while participants were presented with feedback and were requested to maintain attention throughout. Prior to the start of the fMRI task, there was an initial period of 40 seconds of dummy scans which were immediately discarded. The fMRI task is outlined in Figure 3.4. In total, 24 blocks (12 active, 12 rest) were presented during the protocol. Each active block consisted of stimulus presentation of 5 back-to-back trials (referred to as images from this point forward) of 8 secs each, totalling 40 secs, followed by a rest period of 40 secs, during which participants viewed a fixation cross and were instructed to clear their minds. The order of the blocks and back-to-back images (within the blocks) were not presented in a counterbalanced or randomised order.

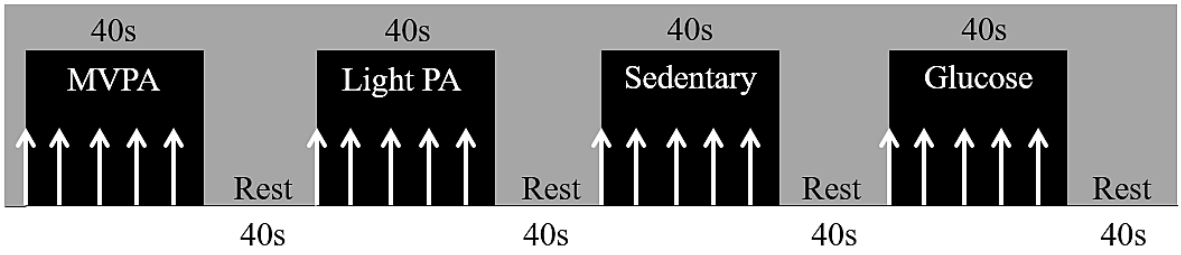

Figure 3.4. An outline of the trial setup including 8 of the 24 blocks presented

Functional MRI data acquisition

Brain imaging data were acquired on a 3T Discovery MR750w scanner (General Electric) using a 32-channel head coil at the National Centre for Sport and Exercise Medicine, Loughborough University, United Kingdom. Structural images (T1-weighted) were acquired using a fast-spoiled gradient echo (FSPGR) Bravo sequence (3D volume, FSPGR; TR=8.2 ms; TE=3.1 ms; matrix size 240×240; 160 sagittal slices; FOV=240 mm; 1 mm thick). One functional scan lasting 16 minutes (480 volumes) was acquired during the task (2D gradient echo EPI; TR=2000 ms; TE=30 ms; flip angle=75 degrees; matrix size 64×64; 35 axial slices; FOV=205 mm; 3 mm thick). Stimulus presentation and synchronisation to scanner acquisition were performed using the software program Presentation version 18.1 (Neurobehavioral Systems Inc).

Behaviour change techniques

During the fMRI appointment, participants will be presented personalised feedback about their physical activity levels, sedentary behaviour and interstitial glucose levels. In line with Michie et al's taxonomy, this study encompassed the following behaviour change techniques: self-monitoring of behaviour, self-monitoring of outcome(s) of behaviour and biofeedback.

Data analysis

Functional MRI

Functional MRI data analysis

Functional data were pre-processed and analysed using statistical parametric mapping (SPM12, Wellcome Department of Cognitive Neurology). All data reported are from scans that exhibited ≤3 mm in translational movement. Data were processed using a standard statistical parametric mapping approach, which consisted of scan realignment, co-registration, segmentation, normalisation, and smoothing. Data were spatially aligned to the first functional image using 4th degree B-spline interpolation. Scans were then co-registered (mean functional image aligned with T1 then parameters applied to all functional images). Functional images were normalised into the Montreal Neurological Institute (MNI) standard stereotactic space with parameters applied to all functional images. A final smoothing step with a Gaussian Kernel with full width half maximum of 8 mm was applied to improve signal-to-noise ratio. The onsets and durations of each of the conditions of interest were modelled according to the block design described in the protocol. For each participant, brain activation was estimated using a general linear model (GLM) and included movement parameters (3 translations, 3 rotations) and a session constant as regressors. All regressors were convolved with SPM12's canonical difference of the hemodynamic response function. Data were high-pass filtered with a cut off of 128 seconds to remove low-frequency noise and slow drifts in the signal. Family-wise error (FWE) correction was used to correct for multiple comparisons at P_{FWE}<.001 and P_{FWE}<.05 for the initial contrasts of interest and the additional contrasts, respectively. At the first level for each participant, contrasts were computed using a series of univariate analyses of covariance (ANCOVAs), averaging activity across the topics compared with baseline (i.e. (1) MVPA>baseline, (2) light physical activity>baseline, (3) sedentary>baseline, (4) glucose>baseline, and (5) behaviour>baseline). Additional contrasts were computed using a series of univariate ANCOVAs, averaging activity between the different blocks of stimuli (i.e. MVPA>light physical activity and glucose>sedentary) and reverse contrasts also computed (i.e. light physical activity>MVPA and sedentary>glucose).

Second level random effects models for each task were constructed that averaged across participants and were subjected to further region of interest (ROI) and between-group analysis. Exploratory whole brain searches were conducted for each contrast with a threshold set at *P*<.001 and *P*<.05 for the baseline contrasts and intergroup contrasts, respectively (cluster threshold of k=0 voxels). Between-group analyses were conducted to compare gender

differences and differences between those least (<150 minutes of bouted MVPA/week) and most (≥150 minutes of bouted MVPA/week) active. Using independent samples *t* test analysis, brain regions were labelled according to the MNI anatomic labelling tool in the Wake Forest University Pickatlas (WFU Pickatlas) (Tzourio-Mazoyer et al., 2002). The average beta parameter estimates of activity during the presentation of information compared with other information blocks were extracted using MarsBaR, an ROI toolbox. All models controlled for centred demographic variables (centred age and sex). An additional centred variable (number of daily glucose scans) was included within the additional contrasts conducted.

Statistical analysis

To examine demographic and self-report data, we conducted descriptive analyses using SPSS version 22.0 (IBM Corp). Repeated measures ANCOVAs were conducted to assess changes in behaviour (levels of MVPA, light physical activity, and sedentary behaviour) from baseline to follow-up, controlling for global wear time (average wear time). Tests of statistical significance conducted with alpha set to 0.05.

Correlation analysis

Parameter estimates corresponding to each significantly activated region, identified via fMRI analysis, were extracted for each participant. Linear regressions provided partial correlation coefficients between the parameter estimates from the significant regions of interest and subsequent behaviour at follow-up (i.e. time spent in MVPA, light physical activity, and sedentary), controlling for wear time. The relationships between behaviour change and activity from the ROIs were examined in separate models for each ROI and the analyses were repeated to assess behaviour via both accelerometry and inclinometry data.

3.4. Results

Participant characteristics

A flow chart of individuals through the study and the characteristics of the sample are presented in Figure 3.5 and Table 3.1, respectively. Four participants were excluded from fMRI analyses due to incorrect scanner parameter setup, poor participant vision (without glasses), and presence of an unsafe magnetic resonance implant. One participant fell asleep, and an additional participant was excluded due to incorrect accelerometry initialisation. This resulted in a final sample of 28 participants.

The 28 participants (43% male) had a mean age of 45.1±9.4 years (range 30 to 59 years). Twenty (71%) received a bachelor's degree or higher, 3 (11%) participants completed secondary school and 5 (18%) completed some additional training. Twenty-five (89%) were White, 2 (7%) were Chinese, and 1 (4%) was Asian or Asian British. Males were significantly taller (178.7 versus 167.5 cm), had a lower body fat percentage (18.8% versus 32.6%), and scanned the Freestyle Libre more frequently (11.7 versus 9.1 scans/day).

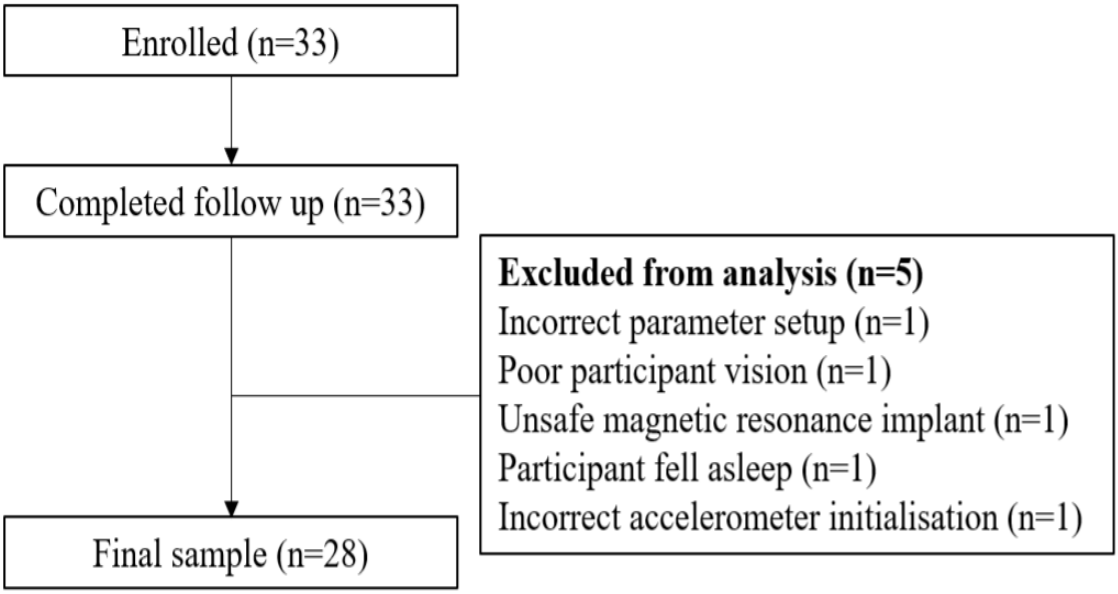

Figure 3.5. A flow chart of how participants progressed through the study

Table 3.1. Participant baseline characteristics, reported as mean±SD

	Whole Sample (n = 28)
Body composition	
Height (cm)	172.3±10
Weight (kg)	75.2±15.3
Body mass index (kg/m^2)	25.2±4.3
Body fat (%)	26.7±9.3
Waist circumference (cm)	85.7±11.3
Cardio-metabolic	
Systolic blood pressure (mmHg)	119.1±11.4
Diastolic blood pressure (mmHg)	72.8±7.2
Resting heart rate (bpm)	60.3±11.2
HbA1c (%)	5.4±0.4
Glucose (mmol/L)	5±0.6
Total cholesterol (mmol/L)	4.8±0.9
Triglycerides (mmol/L)†	0.9±0.2
HDL cholesterol (mmol/L)	1.5±0.4
Glucose monitoring	
Average glucose (mmol/L)	5±0.5
Area under the curve (units)	37.2±27.9
Time in range (%)	88.3±8.1
Scan count (per day)	10.3±4.3
Feedback – attainment of targets	
Number of participants achieving ≥100% of the MVPA guidelines N(%)	11 (39.3)
Number of participants achieving ≥100% of the steps guidelines N(%)	9 (32.1)
Number of participants achieving ≤100% of the sedentary guidelines N(%)	4 (14.3)
Number of participants achieving ≥90%[a] of glucose target range N(%)	13 (46.4)

Abbreviations: HbA1c, glycated haemoglobin; HDL, high-density lipoprotein; mmol/L, millimoles per litre. † n=23 as n=5 measures were outside of measuring range. [a] No participants reported 100% of target range for glucose levels so the threshold was brought down to 90%.

Activated brain regions

First, we contrasted each of the four topics with a fixation cross. The brain regions significantly activated in response to the initial contrasts of interest are presented in Table 3.2. Regions

include the middle and inferior occipital gyrus, middle frontal gyrus, lingual gyrus, subgyral, and thalamus (*P*<.001). No significant voxels were identified between those most and least active or between males and females.

Table 3.2. Average contrasting differences[a] compared with baseline

Region	Hem	x	y	z	Voxels	Z	t	P_{FWE}
MVPA > Baseline								
Middle Occipital Gyrus	L	-38	-74	-14	178	6.29	9.99	<0.001
Lingual Gyrus	L	-14	-94	-10		6.25	9.89	< 0.001
Inferior Occipital Gyrus	L	-22	-90	-14		6.21	9.76	< 0.001
Sub-Gyral	R	36	-62	-16	11	6.06	9.29	< 0.001
Fusiform Gyrus	L	-36	-54	-16	9	5.97	9.03	< 0.001
Sub-Gyral	R	34	-84	-6	93	5.95	8.97	< 0.001
Lingual Gyrus	R	24	-92	-10		5.86	8.74	< 0.001
Lingual Gyrus	R	16	-90	-8		5.63	8.11	0.001
Inferior Occipital Gyrus	R	44	-76	-12	2	5.62	8.09	0.001
Middle Occipital Gyrus	R	30	-88	4	1	5.57	7.97	0.001
Light PA > Baseline								
Cuneus	L	-16	-96	-2	101	6.47	10.61	<0.001
Middle Occipital Gyrus	L	-32	-84	-14	119	6.23	9.80	<0.001
Middle Occipital Gyrus	L	-38	-72	-14		6.05	9.28	<0.001
Sub-Gyral	R	34	-84	-6	83	6.05	9.26	<0.001
Middle Occipital Gyrus	R	30	-84	-14		5.68	8.24	0.001
Middle Occipital Gyrus	R	46	-76	-10	23	6.01	9.14	<0.001
Sub-Gyral	R	36	-62	-16	23	5.90	8.83	<0.001
Middle Occipital Gyrus	R	28	-98	6	19	5.77	8.48	<0.001
Fusiform Gyrus	L	-36	-54	-16	3	5.77	8.47	<0.001
Fusiform Gyrus	L	-34	-50	-18	2	5.70	8.30	<0.001
Inferior Frontal Gyrus	L	-54	18	20	4	5.69	8.27	<0.001
Lingual Gyrus	R	16	-90	-10	10	5.65	8.18	0.001

Region	Hem	x	y	z	Voxels	Z	t	P_{FWE}
Sedentary > Baseline								
Middle Occipital Gyrus	L	-36	-72	-16	19	5.99	9.11	<0.001
Inferior Occipital Gyrus	L	-38	-82	-10	46	5.95	8.98	<0.001
Sub-Gyral	L	-20	-94	-6	36	5.87	8.77	<0.001
Middle Occipital Gyrus	R	36	-84	-4	4	5.78	8.50	<0.001
Inferior Frontal Gyrus	L	-48	14	22	3	5.65	8.16	0.001
Middle Occipital Gyrus	R	48	-76	-10	3	5.59	8.02	0.001
Sub-Gyral	R	28	-88	-6	1	5.57	7.97	0.001
Glucose > Baseline								
Cuneus	L	-16	-96	-6	218	6.69	11.38	<0.001
Middle Occipital Gyrus	L	-36	-74	-16		6.13	9.50	<0.001
Middle Occipital Gyrus	L	-20	-90	-14		5.90	8.83	<0.001
Sub-Gyral	R	36	-62	-16	13	5.99	9.10	<0.001
Lingual Gyral	R	14	-90	-8	28	5.97	9.05	<0.001
Sub-Gyral	R	28	-84	-6	56	5.88	8.78	<0.001
Middle Frontal Gyrus	L	-40	10	30	6	5.69	8.27	<0.001
Middle Occipital Gyrus	R	44	-76	-14	1	5.60	8.05	0.001
Middle Occipital Gyrus	R	30	-84	-14	2	5.58	8.00	0.001
Behaviour > Baseline								
Middle Occipital Gyrus	L	-38	-72	-16	272	6.44	10.49	<0.001
Cuneus	L	-16	-96	-6		6.33	10.12	<0.001
Middle Occipital Gyrus	L	-32	-84	-14		6.07	9.33	<0.001
Sub-Gyral	R	36	-62	-16	27	6.16	9.61	<0.001
Sub-Gyral	R	34	-84	-6	135	6.14	9.53	<0.001
Lingual Gyral	R	22	-92	-10		5.85	8.69	<0.001
Middle Occipital Gyrus	R	30	-84	-14		5.75	8.42	<0.001
Superior Parietal Lobule	L	-32	-62	58	5	6.06	9.28	<0.001
Middle Occipital Gyrus	R	46	-76	-12	24	5.96	9.00	<0.001
Middle Occipital Gyrus	R	48	-66	-14		5.88	8.79	<0.001
Fusiform Gyrus	L	-36	-54	-16	8	5.95	8.98	<0.001

Region	Hem	x	y	z	Voxels	Z	t	P_{FWE}
Middle Frontal Gyrus	L	-52	26	26	9	5.73	8.38	<0.001
Thalamus	R	22	-28	-2	2	5.69	8.27	0.001

Abbreviations: L, left; hem, hemisphere; MVPA, moderate-to-vigorous physical activity; PA, physical activity; R, right. [a] threshold set to p<0.001, cluster threshold of k = 0 voxels. Hem relates to which hemisphere the brain region was identified (i.e. left or right). X, Y and Z relate to the Montreal Neurological Institute (MNI) coordinates that relate to the brain region listed. Voxels refers to the total number of voxels identified as significant in that brain region. Z reflects the z-score and t reflects the t-statistic whilst P_{FWE} is the p-value after accounting for family wise error (i.e. multiple comparisons). Behaviour refers to the inclusion of light physical activity, MVPA and sedentary behaviour.

We then proceeded to the main analysis that contrasted the topics between themselves. The brain regions identified as significantly activated are presented in Table 3.3. Of the additional contrasts of interest, the glucose>behaviour contrast highlighted significant activation in the middle frontal gyrus (–32, 36, –12, z=5.60) and left subgyral (–26, 48, 4, z=5.33). The glucose>sedentary contrast revealed significant activation in the cuneus (–2, –80, 4, z=5.05), middle frontal gyrus (–32, 36, –12, z=4.95; –20, 34, 42, z=4.94), superior frontal gyrus (–26, 50, 4, z=4.79), and right subgyral (28, –52, 24, z=4.66) (Figure 3.6, Table 3.3).

Table 3.3. Average contrasting differences between blocks of stimuli (controlling for age, gender and daily scans)[a]

Region	Hem	x	y	z	Voxels	Z	t	P_{FWE}
Glucose > Behaviour								
Middle Frontal Gyrus	L	-32	36	-12	25	5.60	8.17	< 0.001
Sub-Gyral	L	-26	48	4	16	5.33	7.48	< 0.001
Glucose > Sedentary								
Cuneus	L	-2	-80	4	34	5.05	6.85	< 0.001
Middle Frontal Gyrus	L	-32	36	-12	8	4.95	6.63	< 0.001
Middle Frontal Gyrus	L	-20	34	42	11	4.94	6.61	< 0.001
Superior Frontal Gyrus	L	-26	50	4	3	4.79	6.29	< 0.001
Sub-Gyral	R	28	-52	24	1	4.66	6.04	< 0.001

Abbreviations: L, left; hem., hemisphere; MNI, Montreal Neurological Institute, MVPA, moderate-to-vigorous physical activity; R, right. [a] threshold set to p<0.05, cluster threshold of k = 0 voxels. Hem relates to which hemisphere the brain region was identified (i.e. left or right). X, Y and Z relate to the Montreal Neurological Institute (MNI) coordinates that relate to the brain region listed. Voxels refers

to the total number of voxels identified as significant in that brain region. Z reflects the z-score and t reflects the t-statistic whilst P_{FWE} is the p-value after accounting for family wise error (i.e. multiple comparisons). Behaviour refers to the inclusion of light physical activity, MVPA and sedentary behaviour.

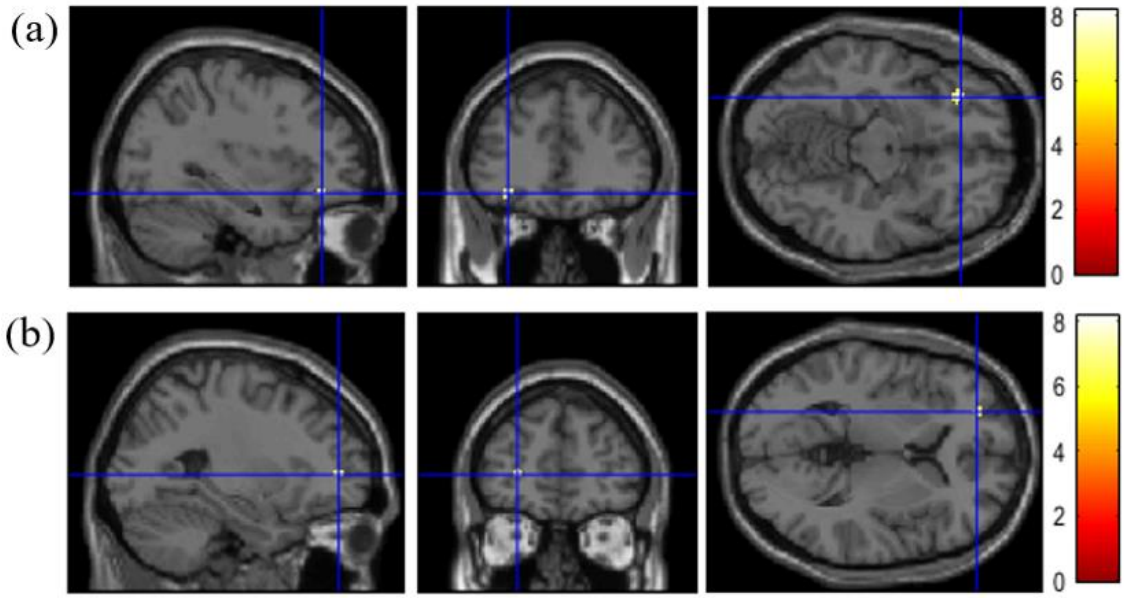

Figure 3.6. An illustration of group activation for glucose>behaviour at (a) -32, 36, -12 and (b) -26, 48, 4

Behaviour change

The behavioural characteristics obtained via accelerometry and inclinometry are presented in Table 3.4. Among the 28 participants, 100% provided ≥4 days for accelerometry during baseline and follow-up. In contrast, only 15 (54%) and 20 (71%) participants provided ≥4 valid days at baseline and follow-up with the inclinometer, respectively, revealing a reduced sample (13 vs 28). As a result, the criteria for the Lumo was adjusted to ≥1 valid days (hereby identifying the limitation for using the LUMO as a data logger). From baseline to follow-up, wear time and sedentary time reduced while minutes of MVPA and counts per minute increased. After controlling for global wear time, only time spent sedentary remained significant for both the accelerometry and inclinometry (589±13.9 min vs 560±11.7 min, *P*=.014 and 602.2±19.4 min vs 554.5±18.1 min, *P*=.001, respectively). Despite a lack of change at the whole sample level for time spent in light physical activity, MVPA, and step count, 9 (32%), 17 (61%), and 16 (57%) participants, respectively, positively increased the amount of steps, light physical activity, and MVPA at follow-up (unadjusted for global wear time). Males accumulated significantly more vigorous physical activity compared with females at baseline

and follow-up (*P*=.029 and *P*=.026, respectively) and also significantly more minutes of MVPA (*P*=.033) at follow-up. No significant associations were observed between number of scans and changes in behaviour via accelerometry or inclinometry (controlling for global wear time).

Table 3.4. Behavioural characteristics, reported as mean±SD

	Accelerometry (n=28)		Inclinometry (n=23)	
	Baseline	Follow Up	Baseline	Follow Up
Number of Valid Days	7±0	7±1	4.2±2.1	5.5±1.7
Wear Time	903.5±67.7	868.2±70.4*	924.3±61.9	884±61.6*
Step Count	9065±3456	9634±3699	8661±2996	9580±4326
CPM	388.1±174.7	410±182.8*	-	-
Sedentary (min)	589.0±84.7	560±75.6*	602.2±91.1	554.5±89.4*
Light PA (min)	265±69	254.2±71.1	-	-
Moderate (min)	45.8±31	50.7±33.2	-	-
Vigorous (min)	3.6±6.6	3.2±6.2	-	-
MVPA (min)	49.4±34.2	53.9±35.5*	-	-
LVPA (min)	314.4±66.4	308.1±72.1	-	-
Stepping (min)	-	-	93.5±26.7	103.2±44.1
Standing (min)	-	-	228.5±98.5	226.5±67.8

*Abbreviations: CPM, counts per minute; LVPA, light-to-vigorous physical activity; MVPA, moderate-to-vigorous physical activity. *, p<0.05*

Functional MRI correlations

To investigate the relationship between brain activation and subsequent behaviour, parameter estimates were calculated for the patterns of neural activation. Of these, only glucose feedback was positively associated with subsequent minutes of MVPA (*r*=0.392, *P*=.043). No significant associations were observed for the inclinometry data.

3.5. Discussion

Summary

As recent neuroimaging work has highlighted value in analysing individual responses to feedback relating to lifestyle behaviours (Falk et al., 2010), we used fMRI to examine neural responses to personalised feedback relating to physical activity, sedentary behaviour, and interstitial glucose levels. We also investigated associations between neural activity and subsequent behaviour. This study lies at the intersection of 3 rapidly evolving areas of interest: wearables, lifestyle behaviours, and neuroimaging. Our study identified that presenting people with personalised feedback relating to interstitial glucose levels resulted in significantly more brain activation when compared with personalised behavioural feedback.

Activated regions of the brain

Our findings identified activations within regions of the prefrontal cortex, in particular the middle frontal gyrus, subgyral, cuneus, and superior frontal gyrus upon comparison of personalised glucose feedback with behavioural feedback. Previous studies have also identified regions within the prefrontal cortex following exposure to antismoking images (Cooper et al., 2015), messages encouraging sunscreen use (Falk et al., 2010), and informative nutritional labels (Enax et al., 2015). The authors hypothesized that the mPFC and precuneus/posterior cingulate regions would be activated in our study given the presentation of personalised feedback (Johnson et al., 2002; Northoff et al., 2006; Northoff & Bermpohl, 2004; Phan et al., 2004; Wang & Hamilton, 2014). Other fMRI studies have identified alternate activated regions including the ventromedial prefrontal cortex, inferior frontal gyrus, and amygdala when presented information about other lifestyle behaviours (e.g. smoking) (Dinh-Williams et al., 2014; Falk et al., 2015; Newman-Norlund et al., 2014). The findings suggest that the personalised feedback did not offer identical regions of interest when compared with the literature; however, some activation did overlap with the mPFC. Neuroimaging studies impose additional complexity because identical neural patterns can result after exposure to different stimuli (Tognoli & Kelso, 2015). However, the identified regions of brain activation may also differ because the stimuli differ between fMRI studies. Our study used a combination of text and images to inform participants about their physical activity, sedentary behaviour, and interstitial glucose levels. In comparison, Falk and colleagues presented images with text and numbers in a sentence (multiple lines of text) (Falk et al., 2015). Overall, our findings suggest that it is possible to identify what brain regions are activated in response to personalised

feedback and that glucose-related feedback evoked more brain activation. As a result, wearable technologies presenting personalised glucose feedback may be useful to employ in future interventions.

Investigating how individuals responded to personalised health-related feedback was an important component of this study as it has been well documented that receiving tailored feedback can result in greater resonance and consequently result in desirable health behaviours (Brug et al., 1996; Skinner et al., 1994; Strecher et al., 1994). Our study demonstrated that presenting feedback pertaining to an individual's glucose levels elicited significantly more brain activation within the middle frontal gyrus and subgyral compared with the behavioural feedback. These regions, anatomically positioned within Brodmann areas 9/10 and 47, respectively, have previously been associated with the actions of making personal moral judgments (Greene & Haidt, 2002) and working memory (d'Esposito et al., 1998), respectively. Previous studies have investigated messages promoting child vaccinations against measles-mumps-rubella and identified that highlighting the dangers of not vaccinating may actually be counterproductive (Nyhan et al., 2014); therefore, findings are often highly dependent on the topic investigated. Future studies could investigate the role of self-affirmation, a construct suggested to increase individual sensitivity to health-risk information and incorporated in prior neuroimaging studies (Cooper et al., 2015; Falk et al., 2015). Self-affirmation essentially investigates how neural activity patterns vary to information after being exposed to personally important values (e.g. friends, family, and religion). Given that the desirable outcome is for people to positively respond to health-related information, exposing a person to their personal values may provoke attention and enhance the importance of the information being given. Therefore, future investigation into whether self-affirmation could contribute to increasing the level of resonance toward personalised feedback and encourage positive behaviours may be crucial.

Behaviour change and associations with brain activation

Our study identified a significant reduction of 29 minutes (or 47 minutes using inclinometry) in time spent sedentary from baseline to follow-up. Previous findings support this finding, having observed a 39.6 min/day reduction in time spent sedentary (Chu et al., 2016). However, no significant differences were observed for time spent in MVPA, light physical activity, or step count. Wearable technologies research to date has offered the suggestion that people can increase their activity levels having received feedback about behaviour (Bravata et al., 2007; Stephenson et al., 2017). However, it must be acknowledged that physical activity, for example,

has been categorised as a very complex behaviour and no single metric can encapsulate a person's level of physical activity (Thompson et al., 2015). According to the literature, changes in behaviour most likely occur when personalised health messages are presented in moments when action can be taken (e.g. at midday to promote a walk following the consumption of lunch) (Patel et al., 2015). Despite participants being presented personalised feedback, there are a multitude of reasons as to why they may or may not have changed their behaviour during the follow-up period. Therefore, determining whether their behaviour (change or no change) was because of the exposure to health-related information is truly unknown. However, emphasising that the feedback was only briefly presented and within an unusual situation (i.e. inside an MRI scanner) is warranted when comparing how people normally receive personalised feedback through wearable technologies. Further investigation could quantify or contextualise the follow-up period to try and account for extraneous variables (e.g. weather, holiday, illness) or consider the inclusion of a control group to provide more definitive findings.

In regard to the relationship of activation and subsequent behaviour during the follow-up period, findings identified a positive partial correlation with minutes of MVPA. Previous studies have investigated behaviour change subsequent to fMRI and have demonstrated positive associations between neural response (e.g. to aversive smoking-related images) and smoking cessation (Falk et al., 2011; Jasinska et al., 2012). For example, Falk and colleagues identified that greater reductions in sedentary behaviour aligned with greater activity in the ventromedial prefrontal cortex, suggesting that if people exhibited greater levels of activation in response to the visual stimuli, those individuals were subsequently more likely to be less sedentary (Falk et al., 2015). On a larger scale, identifying what stimuli (i.e. health messages) evoke positive behaviours (e.g. being less sedentary or more active) can inform the provision of effective public health messages. It could be suggested that, despite the observed association, being presented personalised feedback about health and behaviour while inside an MRI scanner is not a normal environment. Consequently, alternate neuroimaging tools could be useful for future investigation within a free-living setting. For instance, individuals could obtain personalised feedback via a wearable device or a smartphone app while their neural activity is recorded by a portable electroencephalogram system via functional near infrared spectroscopy or by eye tracking (to monitor gaze patterns and fixations). Interestingly, eye tracking has previously been conducted on various health communication materials including both cigarette advertising (Krugman et al., 1994) and nutrition labels (Oliveira et al., 2016).

Strengths and limitations

Positioned at the intersection of several evolving interest areas, this interdisciplinary study offers a number of strengths. One strength was presenting personalised feedback pertaining to both movement behaviours and physiology to participants. These components were objectively measured during baseline and follow-up using novel digital health technologies, obtaining data to directly inform the feedback. In addition, some of the information that was presented in the fMRI tasks were designed based on feedback commonly presented via wearable devices or smartphone apps, reflecting what could be received in real-time in a real-world setting. Future efforts should consider how best to ensure the feedback metrics are meaningful (i.e. standalone) and truly encapsulate physical activity, sedentary behaviour and glucose regulation. It may be worthwhile considering the incorporation of public engagement to co-produce and design these materials. Objective quantification of behaviour at follow-up permitted the assessment of behaviour following exposure and associations between neural activation and behaviour.

Limitations of our study include the situation that participants viewed their glucose levels during baseline wear, an unavoidable situation given intentions to minimise data loss. This protocol confirms that participants had prior exposure to the glucose-related feedback subsequently presented during fMRI. However, to help try and account for this, analysis included the number of scans as a covariate because we thought the number of scans suggested the frequency with which participants viewed their glucose levels (e.g. more scans equalled more exposure and so a greater awareness of their glucose levels). Another limitation was that participants were provided a copy of the education booklet prior to baseline. Despite being instructed to access this resource one week prior to their fMRI appointment, it is possible that participants read this material prior to baseline. In addition, there was a delay between participants completing baseline and attending the fMRI appointment which may have impacted the potential perceived relevancy of the feedback. Following the composition of our sample, it would have been beneficial to exclude individuals who self-reported themselves as active to enhance the opportunity for individuals to feel able to increase their levels of physical activity. Furthermore, our unpowered sample size was another limitation, as we are unable to offer definitive interpretation of the findings. Finally, the pattern of neural activity observed and related psychological processes should be interpreted with caution due to the nature of reverse inference (Poldrack, 2006). Future studies could investigate neural activity in polar groups of people classified by activity or time spent sedentary and to repeat fMRI, so patterns of brain activation are quantified before and after exposure to the feedback.

3.6. Conclusions

This multidisciplinary study highlighted that fMRI can be used to assess the neural response to personalised health feedback. In particular, greater activation in the prefrontal cortex during exposure to glucose compared with behavioural feedback was observed. A reduction in time spent sedentary and a positive association between the parameter estimates and subsequent minutes of MVPA were observed. Future research deploying behavioural feedback in parallel with physiological feedback to encourage positive behaviour change is warranted.

Chapter Four

Study Three:

Sensing Interstitial Glucose to Nudge Active Lifestyles (SIGNAL): Feasibility of combining novel self-monitoring technologies for persuasive behaviour change

N.B. Study protocol has been published (Appendix F).

4.1. Introduction

In England, the prevalence of type 2 diabetes has increased from 2.3 million in 2013 to 3 million in 2016 (NHS Digital, 2016). More alarming still, the prevalence of prediabetes, a preclinical stage comprising impaired glucose tolerance and impaired fasting glucose, has increased more than three-fold from 2003 to 2011, burdening more than one-third of UK adults (Mainous et al., 2014). These trends are global in reach and as a result, 592 million individuals worldwide are projected to be diagnosed with type 2 diabetes by 2035 (Guariguata et al., 2014). Given this, developing successful interventions to prevent type 2 diabetes is a crucial public health priority (Barry et al., 2017) given that 5-10% of people living with prediabetes progress to develop type 2 diabetes annually (Bansal, 2015). To date, structured lifestyle interventions have shown promise in both the prevention and delayed onset of diabetes (e.g. Diabetes Prevention Group, 2002; Norris et al., 2005); however, implementing these interventions into routine clinical settings has proven difficult (Cardona-Morrell et al., 2010).

Over the last decade digital health technologies, most notably wearable activity monitors, have flooded the consumer market and are recognised as a leading trend by industry experts (Ferguson et al., 2015). Smartphone applications (apps) commonly connect with digital health technologies to provide feedback to the user. In 2017 alone, 78,000 new apps were added (16% higher than 2016) bringing the total to 325,000 available health apps (Research2Guidance, 2017). Health apps are becoming increasingly sophisticated most often with a primary function of presenting goal-oriented feedback to offer guidance to the user (e.g. daily step count in relation to 10,000 steps/day). With increasing technological advancement, wearable digital health technologies have evolved to provide feedback not only on movement behaviours but also the physiological consequences of behaviours (e.g. sensors measuring continuous glucose, heart rate and blood pressure). Continual improvements in the sensing elements in digital health technologies provide an opportunity to examine whether coupling these two feedback elements (i.e. movement behaviours and their physiological consequences) could lead to more potent behaviour change messaging and thus warrants further investigation.

A previous study provided thirteen pre-diabetics and type 2 diabetics with information on their glucose concentrations in relation to prescribed bouts of exercise (Bailey et al., 2016). Participants were enrolled into standard care (i.e. self-monitoring exercise using a logbook) or the intervention (standard care plus self-monitoring of glucose using a continuous glucose monitor). Findings highlighted that self-monitoring both exercise and glucose led to greater adherence to the exercise programme over eight weeks compared with individuals self-

monitoring exercise only. Another study provided fifty-two inactive type 2 diabetics 'role model' graphs of glucose levels that identified activity-related reductions in glucose to illustrate the benefits of physical activity (Allen et al., 2008). All participants received 90 minutes of individualised education including topics about diabetes physiology, glucose testing and diet, but the intervention group also wore a continuous glucose monitor for three days at baseline. The intervention group demonstrated a five-minute increase in moderate physical activity at the expense of sedentary time at eight weeks. Collectively, these findings support the potential for providing users with coupled physiological and behavioural feedback. However, to the authors' knowledge, no study has provided individuals with digital health technologies that provide coupled (i.e. simultaneous) feedback on both physical activity and glucose in free-living conditions.

Before large-scale studies providing physiological and behavioural feedback to individuals at risk of developing type 2 diabetes are conducted, the extent to which individuals engage with the intervention needs to be understood. This is important not only for researchers but clinicians and industry alike. With the provision of combined physiological and behavioural feedback in its infancy (i.e. immature), it is important to examine how these individuals engage with digital health technologies and health apps providing this feedback. For example, in a study of over 12 million adult users of a weight loss app 'Lose It!', authors found that those who customised the app to their personal preferences engaged for a longer period of time compared to those who kept the default configuration (Serrano et al., 2017). Such insights into how people naturally engage with digital health technologies may help optimise the delivery of future interventions and promote their incorporation into existing national prevention programmes. Objectively measuring how long people spend on health apps and how they use digital health technologies may permit the identification of sub-groups requiring different levels of support to lead a more physically active lifestyle. Therefore, the present study examined how individuals at moderate-high risk of developing type 2 diabetes naturally engaged with wearable digital health technologies and associated health apps providing continuous, objective physical activity and glucose feedback over six weeks.

4.2. Aims and objectives

Primary aim

To examine participant engagement with physical activity and glucose self-monitoring technologies over 6 weeks; assessed by app usage, scan frequency (glucose), sync frequency (physical activity) and changes to physical activity goals.

Secondary aims

To (i) assess the acceptability and practicality of the intervention trial, (ii) establish levels of physical activity and glucose at baseline, 1, 2, 3, 4, 5, and 6 weeks; (iii) inform the development of a full-scale RCT.

4.3. Methods

Study design

A detailed description of the study protocol has been published (Whelan et al., 2017; Appendix F). Briefly, the seven-week protocol consisted of a baseline period (one week) and an intervention period (six weeks). Following baseline, participants were randomised into one of three groups (described further below) and all participants wore an activity monitor and a glucose sensor during the intervention period (regardless of group allocation). The Loughborough University Ethics Advisory Committee provided ethical approval for the study in April 2017 (Research Proposal R17-P049).

Inclusion criteria

Adults aged ≥40 years, who recorded a moderate-to-high risk of developing Type 2 diabetes on Leicester Risk Assessment screening tool (i.e. ≥16 points out of 47) (Gray et al., 2010) and owned a compatible Android smartphone were eligible to take part. Compatible smartphones were defined as having the following characteristics: An Android operating system of ≥4.0, Near Field Communication (NFC) capability, a screen resolution of 480x800 to 1080x1920 and a screen size of 8.9-14.5cm. These requirements were in place to ensure participants could install the LibreLink app on their smartphone; thereby preventing iOS smartphone owners from taking part. However, it is likely that with continuing app development the need to implement strict smartphone criteria will disappear in the near future. As per LibreLink app guidance, known smartphones (at the time of recruitment) that duly meet the above compatibility criteria

but for some reason do not work were the Samsung Galaxy 7, Samsung S8, Nexus 5X and Nexus 6P.

Exclusion criteria

Individuals were excluded if they had been diagnosed with any form of diabetes, presented with a HbA1c of ≥6.5% at baseline, had suspected/confirmed pregnancy, who were unable or unwilling to provide informed consent, who could not or were unwilling to adhere to the study protocol or could not read and write English.

Recruitment

Interested individuals were recruited between May and September 2017. Participants were initially recruited via community organisations through the distribution of posters, letters and emails sent to existing participant databases within Leicestershire, UK. To further boost recruitment, recruitment efforts (using posters and emails) were also directed toward local businesses and local social media channels (i.e. Facebook and Twitter). Interested individuals were directed to complete a brief online survey to determine level of risk for type 2 diabetes (Gray et al., 2010) via Qualtrics (Qualtrics, Provo, UT). The questions related to sex, age, ethnic background, familial history of diabetes, waist circumference, body mass index and blood pressure (Gray et al., 2010). The waist circumference question was modified to instead ask participants about their clothing size and fit rather than a direct measurement of their waist circumference (in cm). Their responses to these two clothing fit questions were used to calculate an estimated waist circumference value (Battram et al., 2011) which was subsequently used to determine level of risk. Upon completion, moderate (16-24 points out of 47) and high-risk (≥25 points out of 47) individuals self-reporting ownership of a compatible smartphone were contacted and sent a participant information sheet via email. Ineligible individuals were informed of their risk and directed to Diabetes UK risk prevention documentation. Individuals who continued to express an interest in taking part (having read the study material and confirmed eligibility) were contacted about scheduling the baseline appointment.

Intervention groups

Participants were block randomised (3, 6 and 9 block sizes) using a 1:1:1 study allocation ratio into one of three groups (Figure 4.1). Group allocations were concealed from the researcher until participants completed baseline wear in an effort to minimise the introduction of any bias. Participants were informed of their group allocation after completing baseline wear. Group 1

were offered glucose feedback for 4 weeks (G_4) followed by glucose plus physical activity feedback for 2 weeks (GPA_2) (hereon referred to as G_4GPA_2). Group 2 were offered physical activity feedback for 4 weeks (PA_4) followed by glucose plus physical activity feedback for 2 weeks (GPA_2) (hereon referred to as PA_4GPA_2). Group 3 were offered glucose plus physical activity feedback for six weeks (hereon referred to as GPA_6).

It should be acknowledged at this stage that the derivation of these groups followed substantial discussion around which study design would best meet the research question and study budget. We arrived at the conclusion of the study protocol outlined in Figure 4.1 in part by the following factors: the lifespan of the glucose sensors were 2 weeks; intentions to maximise data on participant engagement with the technologies (i.e. decided against a true control group); intended to ensure participant engagement was captured using both devices simultaneously across all participants; two weeks was likely insufficient for initial exposure and total duration appeared long enough to identify behaviour change but not too long for financial outlay.

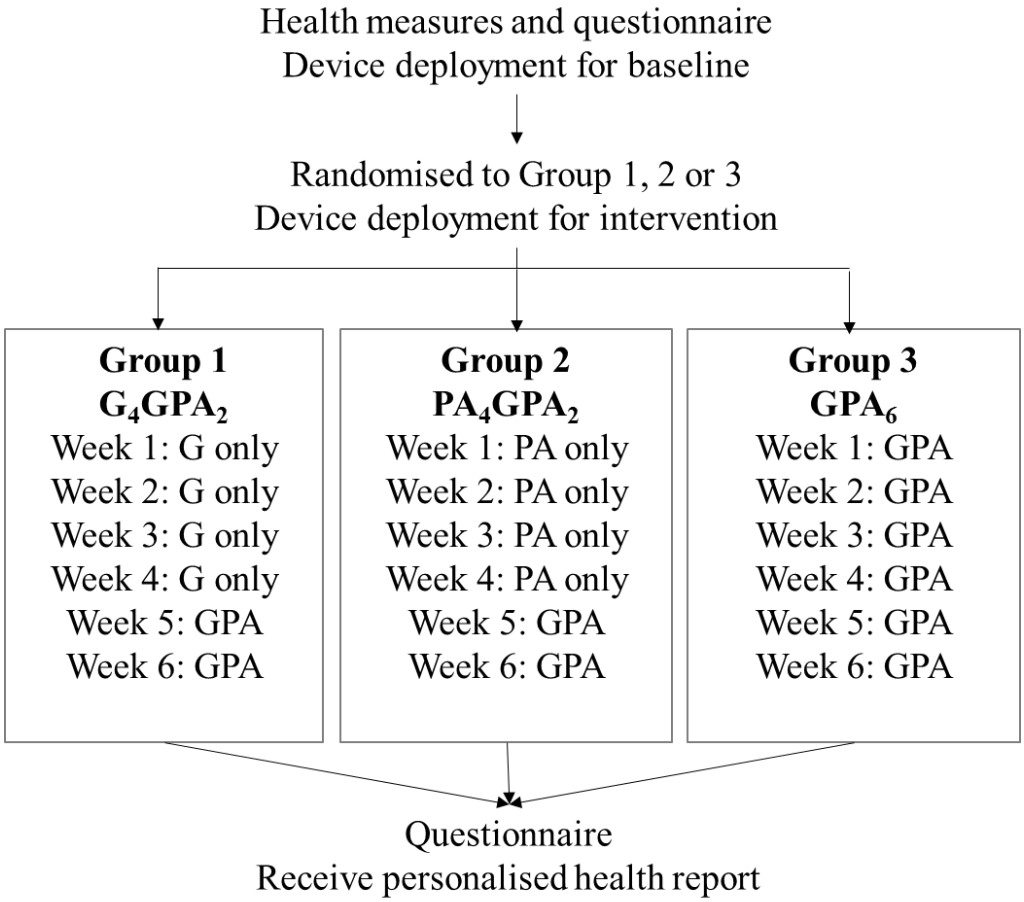

Figure 4.1. An outline of the study protocol. G_4GPA_2 represents glucose feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks); PA_4GPA_2 represents physical

activity feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks) and GPA_6 represents glucose and physical activity feedback (6 weeks). Abbreviations: G, glucose feedback; PA, physical activity feedback; GPA, glucose plus physical activity feedback.

Wearable technologies

Fitbit

Physical activity feedback was provided by a Fitbit Charge 2 (Fitbit Inc., San Francisco, CA) (Appendix G). Participants were asked to wear the Fitbit on their non-dominant wrist during waking hours; removing it for sleep and any water-based activities. Participants were asked to charge the Fitbit overnight every night and to sync the device at least once every five days to minimise data loss. In an effort to monitor participant adherence to charging and syncing, the research team sent participants reminder emails to either charge (if battery level reached <25%) or to sync (if it had been ≥5 days since the previous recorded sync). Battery level was remotely monitored with Fitbit sending emails automatically to the research team when the Fitbit battery reached a critical level (<25%). Fitbit syncs were remotely monitored via the Fitabase dashboard (Small Steps Labs LLC., San Diego, CA) which ordered participant Fitbit accounts by time since last sync; allowing easy identification of participants who had not synced their Fitbit for >5 days. No syncs were extracted for G_4GPA_2 during intervention weeks 1 to 4 to minimise participant interaction with the technology. Devices were initialised using the Fitbit app and the data were downloaded via Fitabase. The raw 60-second epoch data were re-structured to present 1,440 epochs/day. Data were analysed by Kinesoft version 3.3.80 (Kinesoft, Lougborough, UK).

Physical activity feedback was displayed on both the Fitbit screen (wrist) and the participant's smartphone (via the app). The following metrics were viewable: daily step count; floors (flights of stairs) climbed; number of active minutes; number of calories burned (kcal); heart rate and number of hours achieving ≥250 steps. The Fitbit app also provided historical information and more comprehensive information for all of the metrics (e.g. hourly graphs).

Freestyle Libre

Feedback on glucose levels during the intervention period was provided by a Freestyle Libre flash glucose monitor (Abbott Diabetes Care, Alameda, CA) (Appendix G). In total, participants wore three Freestyle Libre sensors (one every two weeks) during the intervention period. These minimally-invasive, disposable sensors were worn on the non-dominant posterior brachium. Participants were asked to scan the sensor using the LibreLink app once

every seven to eight hours (three times per day) as a minimum to avoid data loss. Participants were not prompted at all about their scanning frequency and were able to set reminders to scan via the LibreLink app. No charging or calibration of the sensors was required. Glucose levels were captured by the LibreLink app and extracted in 15-second epochs using Diasend (Diasend Inc., Chicago, IL). No data were recorded for PA_4GPA_2 during the intervention weeks 1 to 4 as participants were not set up with the Freestyle Libre app or asked to scan the device but this will likely become void in future iterations. A valid day was defined as having ≥90% of glucose data and only valid days were carried forward for analyses.

Interstitial glucose levels were categorised as: normal (4.0-5.9 mmol/L), above range (≥6.0 mmol/L) or below range (<4.0 mmol/L) (International Diabetes Federation, 2007). Each participant scan was characterised by the following metrics: glucose level (mmol/L), rate of change (i.e. rising quickly, rising, changing slowly, falling, falling quickly or no trend arrow; thresholds for these metrics not provided by the manufacturer), target zone (normal, above range or below range) and a 24-hour graph of glucose. Glucose feedback was displayed on the LibreLink app only and the following metrics were viewable: glucose levels (value at the time of scanning and a graph of the previous 24 hours); an arrow to suggest rate and direction of change; time spent in target range; number of low glucose events and historical data (e.g. glucose levels on previous days).

Primary outcomes

User engagement

An assessment of participant engagement was conducted to help determine if this unique intervention of coupled feedback warrants further investigation. Participant engagement with the self-monitoring technologies was assessed by time spent on the smartphone apps, the frequency the Freestyle Libre was scanned and the frequency the Fitbit was synced and any changes to the set physical activity goals. The duration of time spent on the study-related apps (Figure 4.2) was recorded in minutes, as either a summary of total time per day or time per visit to the app, dependent on participants' smartphones. As a result, time per day on each app was calculated for all participants. App usage was monitored and extracted using Ethica Data (Kitchener, Ontario, Canada). The frequency the glucose sensor was scanned by the participant was collected by LibreLink app (*compulsory number of scans*: once every eight hours). The frequency that participants synced the Fitbit was collected by Fitabase (*compulsory number of syncs*: once every five days). Prior to deployment, all participants received verbal

and written information about how to scan the Freestyle Libre and how to sync the Fitbit. Default physical activity goals were 10,000 steps, 30 active minutes, 2,500kcal, 10 flights of stairs and 8km per day. Participants were informed how to change these values, if they wished, using verbal instructions and a brief demonstration. To record if, when and how the activity goal settings were changed, the research team accessed the Fitbit account associated with each participant at the end of each day.

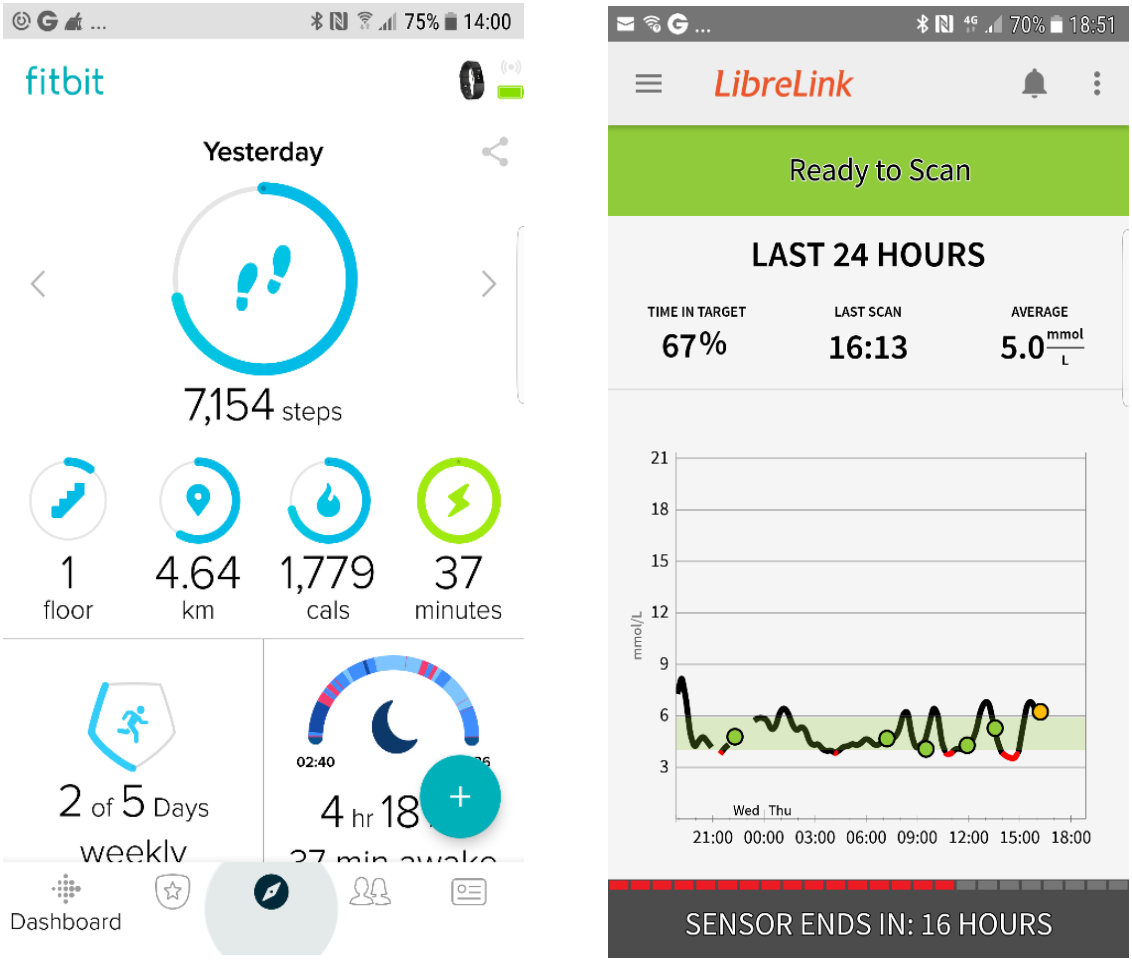

Figure 4.2. Screenshots of the Fitbit app (left) and LibreLink app (right)

Secondary outcomes

Feasibility

Feasibility was also assessed to help identify whether the intervention was suitable using indicators of recruitment, uptake, retention and device wear. The assessment of feasibility focused on the practicality and acceptability of the self-monitoring technologies as outlined by Bowen and colleagues (Bowen et al., 2009).

Practicality

Researcher-produced project records documented the number of additional glucose sensors provided to participants (minimum of three per participant) and reasons why additional sensors were needed (e.g. faulty or displaced sensors). Missing glucose data (reported as percentage data capture, number of missing data events and minutes of missing data) were quantified using raw interstitial glucose data downloaded from Diasend. Missing glucose data occurred if participants failed to adhere to scanning at least once every eight hours. The amount of missing physical activity data was recorded and quantified using Fitabase (Small Steps Labs LLC., San Diego, CA). Missing data for the Fitbit would result in obtaining a truncated daily summary of activity data rather than minute-level data.

Acceptability

Uptake and retention

The number of participants who (a) completed the survey, (b) were eligible, (c) decided to take part (uptake) and (d) completed the study (attended follow-up assessment) were recorded. Non-usage attrition (failure to comply with compulsory engagement but no study withdrawal) and dropout attrition (withdrawn or not attending the final appointment) were assessed (Alkhaldi et al., 2016).

Wear adherence

Fitbit wear time and undirected overnight wear were quantified using minute-level data extracted from Fitabase. Wear time for each epoch was defined by the combined presence of a heart rate signal (>0 beats/min) and not classified as sleep according to Fitbit's default proprietary algorithm.

Smartphone usage

The number of participants consenting to having their phone use monitored via Ethica Health app (Kitchener, Ontario, Canada) were recorded. Of these participants, the number who consent for *full* coverage (all 14 data sources; location sensors, motion sensors, contact network sensors, digital footprint and exit survey) and *restricted* coverage (3 data sources; digital footprint and exit survey) were recorded. The *full* coverage option was the default decision presented to participants and if any participants expressed concerns then they were offered the option of the *restricted* coverage.

Baseline physical activity assessment

ActiGraph

To assess and compare baseline physical activity levels of our participants against nationally representative studies (Chaudhury & Esliger, 2008; Troiano et al., 2008), participants were asked to wear an ActiGraph wGT3x-BT accelerometer (ActiGraph, Pensacola, FL, USA) for seven consecutive days. Participants were instructed to wear these accelerometers around the waist (over the right anterior iliac spine) with an elastic belt during all waking hours and only removed for water-based activities. Initialisation, downloading and conversion of accelerometer files into 60-second epoch were conducted using ActiLife version 6.13.1 (ActiGraph, Pensacola, FL, USA). Kinesoft version 3.3.80 (Kinesoft, Loughborough, UK) was used to batch analyse the 60-second epoch files. Non-wear was defined as 60 minutes of consecutive zeros with up to two minutes of non-zero interruptions allowed (Troiano et al., 2008). Valid files had ≥4 valid days defined as having ≥10 hr/day (Troiano et al., 2008). Stationary time was classified as <100 counts per minute (cpm), light physical activity as 100-2019 cpm and MVPA as ≥2020 cpm (Troiano et al., 2008).

Fitbit

All email accounts and password combinations were manually generated and managed by the research team. During baseline assessment, Fitbits were masked for all participants using black tape and participants were asked not to tamper with it. Settings on the Fitbit app were adjusted to remove the feedback metrics and notifications restricted (Appendix H). Participants had access to the app to allow automatic syncs to occur thereby ensuring minute-level data were obtained.

Levels of technology readiness, health status and attitude

Questionnaires were completed by participants electronically using Bristol Online Surveys (Bristol, UK) at baseline and at the final appointment. Quality of life was assessed via the 26 item EQ-5D-5L (Herdman et al., 2011), technology readiness via the 16 item Technology Readiness Index (TRI 2.0) (Parasuraman & Colby, 2015), diabetes knowledge via the revised diabetes knowledge test (DKT) (Collins et al., 2011) and attitude toward developing diabetes using the general attitudes section of the Risk Perception Survey for Developing Diabetes (RPS-DD) (Walker et al., 2003). The maximum score for the DKT was 18. The TRI2.0 questionnaire classified individuals as either a Skeptic, Explorer, Pioneer, Hesitator or Avoider. Skeptics offered low levels of optimism, discomfort and insecurity but moderate levels of

innovativeness; Explorers offered high levels of optimism and innovativeness but low levels of discomfort and insecurity; Avoiders revealed low levels of optimism and innovativeness but high levels of discomfort and insecurity; Pioneers revealed high levels of optimism, innovativeness, discomfort and insecurity; whilst Hesitators demonstrated high levels of optimism, low levels of innovativeness and moderate levels of discomfort and insecurity.

Other measures

Participant demographics

Self-reported age, sex, ethnic background, employment status, household income, home postcode (used to derive index of multiple deprivation (IMD)) and highest level of education were recorded.

Cardiometabolic health

Participants removed shoes and socks prior to having height measured using a Seca stadiometer (Seca, Hamburg, Germany) and weight and body fat percentage measured using Tanita scales (Tokyo, Japan). Two measures of waist circumference were taken at the midpoint between the lowest rib and top of the iliac crest with an additional measure taken if the difference exceeded 1cm. Glycated haemoglobin (HbA1c) was assessed using an Afinion AS100 Analyser (Alere Inc., Waltham, MA). Three measures of resting blood pressure were recorded using an Omron digital monitor (Omron Corporation, Kyoto, Japan) after participants were seated for ≥10 minutes, with at least 2 minutes rest between measurements. Participants were classified as having hypertension if their resting blood pressure was ≥140/90mmHg (National Institute for Health and Care Excellence, 2011) and as pre-diabetic if their HbA1c reading was 6.0-6.4% (National Institute for Health and Clinical Excellence, 2012).

Physical functioning and aerobic fitness

Upper body strength was assessed by hand grip strength using a handheld Takei dynamometer (Takei Scientific Instruments, Tokyo, Japan). The Canadian Physical Activity, Fitness and Lifestyle Approach grip strength protocol was used (Canadian Society for Exercise Physiology, 2004). Lower body strength was assessed on the dominant leg by the quadriceps maximal voluntary contraction (QMVC) using the DAVID G200 knee extension machine (David Health Solutions Ltd., Helsinki, Finland). Aerobic fitness was assessed using the modified Canadian Aerobic Fitness Test (mCAFT) (Canadian Society for Exercise Physiology, 2004). Participants were excluded from the mCAFT if they were aged ≥70 years, if their blood pressure was more

than 140/95mmHG, if they reported sufficient mobility-related problems or any other contraindications to exercise testing according to the Physical Activity Readiness Questionnaire (Warburton et al., 2011). Stage achieved on the mCAFT was converted to an estimate of O_2 cost, entered alongside age and weight, into an algorithm to calculate predicted VO_{2max} (Weller et al., 1993).

Behaviour change techniques

Prior to starting the intervention, the researcher will implement the default settings for levels of physical activity (BCT 1.1: Goal setting [behaviour]) (i.e. 10,000 steps and 10 floors climbed) and glucose (BCT 1.3: Goal setting [outcome]) (i.e. 4.0-5.9 mmol/L). Participants will also receive haptic feedback (BCT 7.1: Prompts/cues; i.e. a gentle vibration) as a reminder to move by the Fitbit 10 minutes prior to the end of each hour (default 09:00-18:00) if 250 steps have not been taken. In relation to the other behaviour change techniques, participants will be able to monitor physical activity levels using the Fitbit Charge 2 (BCT: 2.3 Self-monitoring of behaviour) and glucose levels using the Freestyle Libre (BCT: 2.4: Self-monitoring of outcome(s) of behaviour) which is a minimally-invasive device that presents feedback about glucose (BCT: Biofeedback).

Statistical analyses

Descriptive statistics were reported as mean (SD) for continuous variables and frequency (%) for categorical variables. Identification of any statistical differences did not necessarily result in their inclusion as covariates within the main analysis (due to small sample size). Analysis of variance (ANOVA) were conducted to compare between intervention groups for continuous variables and chi-square tests for between group comparisons for categorical, unpaired variables. If a significant chi-square statistic was revealed, unadjusted standardised residuals were computed to identify significant pairwise differences. If the unadjusted standardised residuals were >1.96 or <-1.96 then the z-score was classified as significant. McNemar tests were used to assess changes in categorical, paired variables over time. Two-way repeated measures ANOVAs were used to compare between groups over the intervention period. Mauchly's test of sphericity was examined to assess sphericity of the data, with Greenhouse-Geisser statistics used when the assumption of sphericity was violated. Participant engagement metrics were entered as the dependent variable whilst time (within-subject), group (between-subject) and time*group interactions were examined. Two-way repeated measures analysis of covariance (ANCOVA) was used to assess changes in step count over the intervention period

between groups, controlling for global wear time (average wear min/day over seven weeks). Pairwise differences were identified using a post-hoc Bonferroni correction. All data were analysed using Statistical Package for Social Sciences Version 24.0 (SPSS Inc. Chicago, IL) with alpha set to 0.05.

4.4. Results

Participant recruitment

Between 16th May and 30th August 2017, there were a total of 525 visitors to the SIGNAL Study risk assessment website tool. Of these, 340 (64.8%) completed the survey and 58 (17.1% of those who completed the survey) identified as eligible (Figure 4.3). Forty-five individuals (77.6% of those eligible and 13.2% of those completing the survey) consented to take part and no participant withdrawals were recorded. The forty-five participants were recruited via participant databases (n=12), local businesses (n=11), social media (n=10), university employees/alumni (n=8) and word of mouth (n=4).

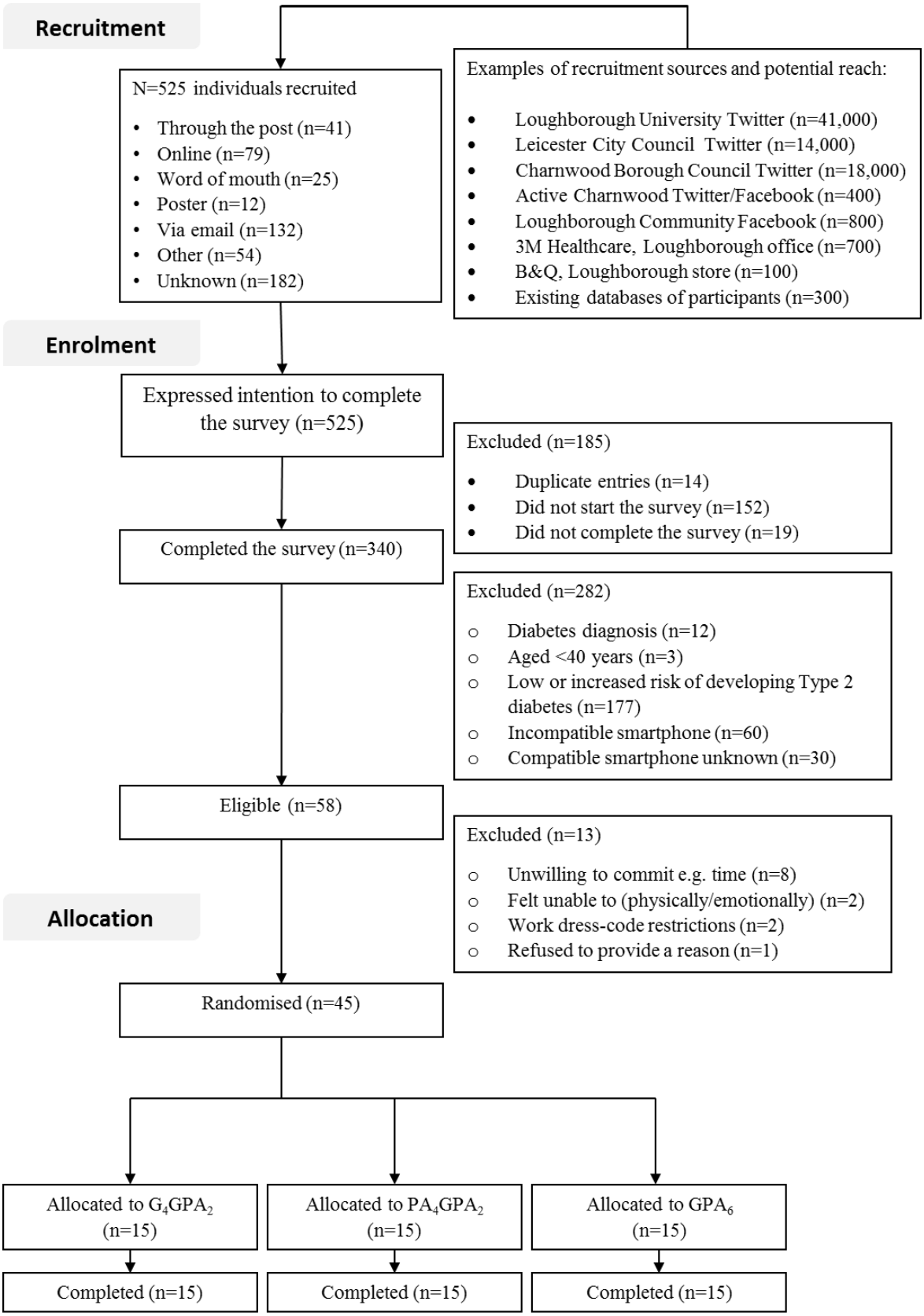

Figure 4.3. A flow diagram of recruitment, enrolment and allocation for the study. G_4GPA_2 represents glucose feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks); PA_4GPA_2 represents physical activity feedback (4 weeks) followed by glucose and

physical activity feedback (2 weeks) and GPA_6 represents glucose and physical activity feedback (6 weeks).

Participant characteristics

Forty-five participants (60% female) had a mean age of 56±8.7 (range: 40-77 years) and most reported themselves as White British (88.9%) (Table 4.1 and Table 4.2). Seven participants (15.6%) were identified as being at high-risk of developing Type 2 diabetes and 3 participants (6.7%) were classified as living with prediabetes. Seventeen (37.8%) were overweight, 13 (28.9%) had obesity and 10 (22.2%) had severe obesity. Seventeen participants (37.8%) were classified as hypertensive. Thirty-nine participants (86.7%) did not comply with the UK physical activity guidelines at baseline.

Table 4.1. Participant baseline demographics stratified by group, reported as mean±SD or N (%)

	Whole Sample (n=45)	G_4GPA_2 (n=15)	PA_4GPA_2 (n=15)	GPA_6 (n=15)
Demographics				
Age (yrs)	56±8.7	58.8±9.8	55.3±8.8	53.9±7
Female gender N (%)	27 (60)	9 (40)	9 (60)	12 (80)
Employment status N (%)				
Employed	30 (66.7)	9 (60)	10 (66.7)	11 (73.3)
Retired	10 (22.2)	4 (26.7)	4 (26.7)	2 (13.3)
Other	5 (11.1)	2 (13.3)	1 (6.7)	2 (13.3)
Education level N (%)				
Undergraduate or higher	24 (46.7)	12 (80)*	3 (20)	9 (60)
Lower than Undergraduate	21 (46.7)	3 (20)*	12 (80)	6 (40)
Household income N (%)				
≥£52,000	19 (42.2)	6 (40)	5 (33.3)	8 (53.3)
£18,000-£51,999	18 (40)	7 (46.7)	7 (46.7)	4 (26.7)
<£18,000	6 (13.3)	2 (13.3)	2 (13.3)	2 (13.3)
Unknown	2 (4.4)	0	1 (6.7)	1 (6.7)
Postcode deprivation N (%)				
≤8.49 (least deprived)	20 (44.4)	6 (40)	7 (46.7)	7 (46.7)
≥34.18 (most deprived)	3 (6.7)	0	1 (6.7)	2 (13.3)
Diabetes knowledge				
DKT test score	10.7±3	11.1±2.5	9.7±3.5	11.3±2.8

*Table notes: G_4GPA_2 represents glucose feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks); PA_4GPA_2 represents physical activity feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks) and GPA_6 represents glucose and physical activity feedback (6 weeks). Abbreviations: DKT, Diabetes Knowledge Test. *, significant difference between G_4GPA_2 and PA_4GPA_2 (p=.004). Postcode deprivation offers ten categories but only the two most extreme categories have been included in this table for presentation reasons.*

Table 4.2. Participant baseline characteristics stratified by group, reported as mean±SD or N (%)

	Whole Sample (n=45)	G_4GPA_2 (n=15)	PA_4GPA_2 (n=15)	GPA_6 (n=15)
Body composition				
Height (cm)	168.4±9.5	171.2±9.4	167±9.6	167±9.6
Weight (kg)	89.6±19.7	86.7±16.1	96.6±23.3	85.5±18.3
BMI (kg/m^2)	31.6±6.9	29.6±4.9	34.8±9.4	30.4±4.3
Waist circumference (cm)	101.5±14.8	98.8±14.3	108.4±15.2	97.4±13.3
Cardio-metabolic health				
Prediabetic (%)	3 (6.7)	1 (6.7)	0	2 (13.3)
HbA1c (%)	5.6±0.3	5.6±0.3	5.5±0.3	5.6±0.3
SBP (mmHg)	132±15.8	135.9±15.1	131.7±16.3	128.5±16.2
DBP (mmHg)	81.7±10.4	82.7±10.6	79.9±9.4	82.3±11.5
Physical function				
Grip strength (combined, kg)	69.1±22.2	75.8±23.1	64.6±21.1	67±22.4
Quadriceps strength (dominant leg, Nm)	124.3±64.1	137.1±73.8	109.4±39.4	125.5±73
Calculated VO_{2max} (ml/kg/min)[a]	36.7±6.7	37.4±8.2	35.5±5.0	37±6.8
ActiGraph physical activity[b]				
Number of valid days	6.6±0.7	6.8±0.8	6.5±0.7	6.5±0.6
Valid day, N (%, c%)				
7 days	31 (68.9, 68.9)	14 (93.3, 93.3)	9 (60, 60)	8 (53.3, 53.3)
6 days	10 (22.2, 91.1)	0 (0, 93.3)	4 (26.7, 86.7)	6 (40, 93.3)
5 days	3 (6.7, 97.8)	0 (0, 93.3)	2 (13.3, 100)	1 (6.7, 100)
4 days	1 (2.2, 100)	1 (6.7, 100)	0 (0, 100)	0 (0, 100)
Wear time (min/day)	861.5±86.9	911.4±88.5*	833.2±74	839.8±80
Step count	6905±3776	7331±3433	5637±1963	7748±5148
CPM	328.7±144.6	342.2±107.6	281.3±123.1	362.5±187.5
Sedentary (min/day)	540.1±95.3	569.9±90.1	536.6±89.9	513.9±103.2
Light PA (min/day)	288.2±83.4	304.4±97.1	271.4±77.3	288.7±76.7
MVPA (min/day)	33.1±28.4	37.0±21.2	25.2±18.6	37.2±40.5
MVPA in bouts ≥10 minutes (min/day)	10.1±21.9	9.6±14.4	5±6.2	15.8±34.5
Met physical activity guidelines[c] N (%)	5 (11.1)	2 (13.3)	1 (6.7)	2 (13.3)
Fitbit physical activity[b]				
Number of valid days	6.7±0.7	6.8±0.8	6.5±0.8	6.8±0.4
Valid day, N (%, c%)				
7 days	36 (80, 80)	14 (93.3, 93.3)	10 (66.7, 66.7)	12 (80, 80)
6 days	7 (15.6, 95.6)	0 (0, 93.3)	4 (26.7, 93.4)	3 (20, 100)
5 days	0 (0, 95.6)	0 (0, 93.3)	0 (0, 93.4)	0 (0, 100)
4 days	2 (4.4, 100)	1 (6.7, 100)	1 (6.7, 100)	0 (0, 100)
Wear time (min/day)	865.1±69.6	912.4±63.3	832±61.1	851±60.7
Step count	8575±4530	9329±4251	7650±4007	8747±5367

Table notes: G_4GPA_2 represents glucose feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks); PA_4GPA_2 represents physical activity feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks) and GPA_6 represents glucose and physical activity feedback (6 weeks). Abbreviations: c, cumulative; CPM, counts per minute; DBP, diastolic blood pressure; MVPA, moderate-to-vigorous physical activity; PA, physical activity; SBP, systolic blood pressure. [a]*N=32, N=13 excluded (n=6, self-reported mobility issues; n=4, resting diastolic blood pressure ≥95 mmHg; n=3, aged ≥70 years); fitness score based on age and sex of each participant.* [b]*unadjusted values are presented.* [c]*150 min/week of moderate-to-vigorous physical activity in bouts of ≥10 minutes (using MVPA in bouts of ≥10 min/day * 7) or 75 min/week of vigorous-intensity physical activity.* [*]*, significant difference between G_4GPA_2 and PA_4GPA_2 (p=.035).*

Primary outcomes

User engagement

Freestyle Libre – scan frequency and characteristics

A key engagement metric for the LibreLink app was how often participants scanned the glucose sensor. The average number of scans each day did not differ significantly between G_4GPA_2 and GPA_6 groups (7.5±4.9 versus 7.7±4.3 scans/day, p=.883; Figure 4.4). However, it was noted that the number of scans/day significantly decreased over the six weeks on average for these groups (9.2±5.1 scans/day in week 1 to 5.9±3.4 scans/day in week 6, p=.016).

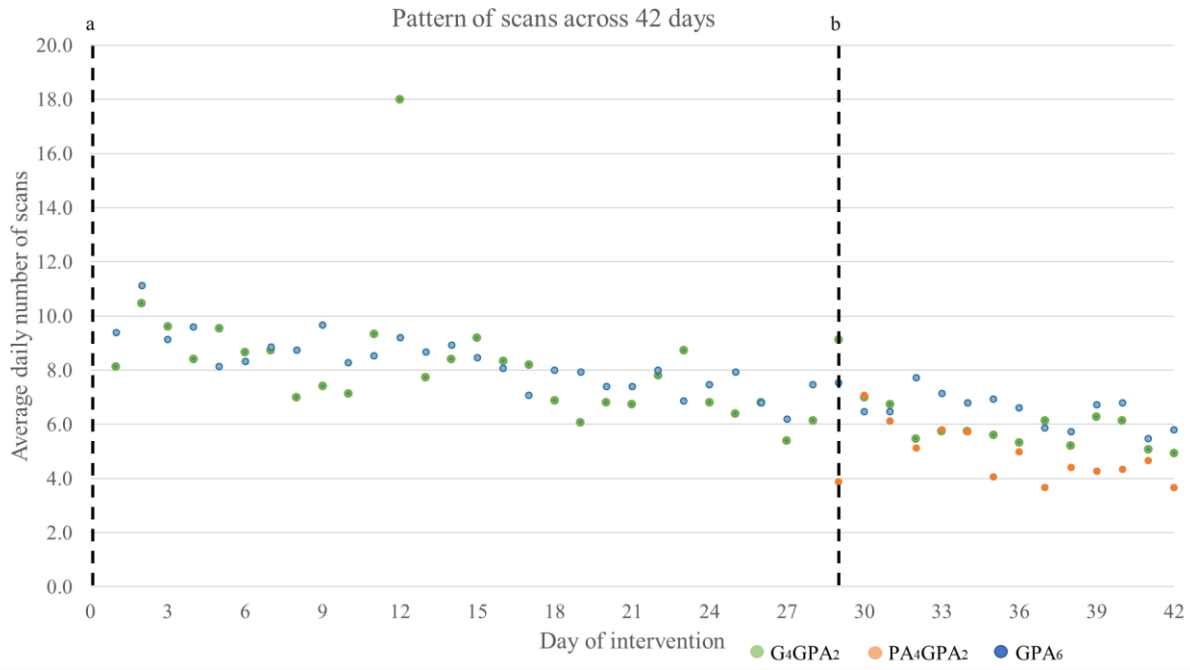

Figure 4.4. Average daily number of Freestyle Libre scans across the intervention period. Figure notes: Point of unmasking glucose feedback at (a) for G_4GPA_2 and GPA_6 and (b) for PA_4GPA_2. Note that the compulsory engagement threshold was 3 scans/day. G_4GPA_2 represents glucose feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks); PA_4GPA_2 represents physical activity feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks) and GPA_6 represents glucose and physical activity feedback (6 weeks).

Figure 4.5 illustrates when participants scanned the glucose monitor across an average 24-hour period. Participants scanned their glucose sensor significantly more often in the morning, afternoon and evening periods compared with overnight (27.9±4.8% vs. 31±4.8% vs. 33.6±6.2% vs. 7.6±7.4%, respectively, p<.001) and most frequently between 21:00-22:00. No other significant differences between times of day were observed.

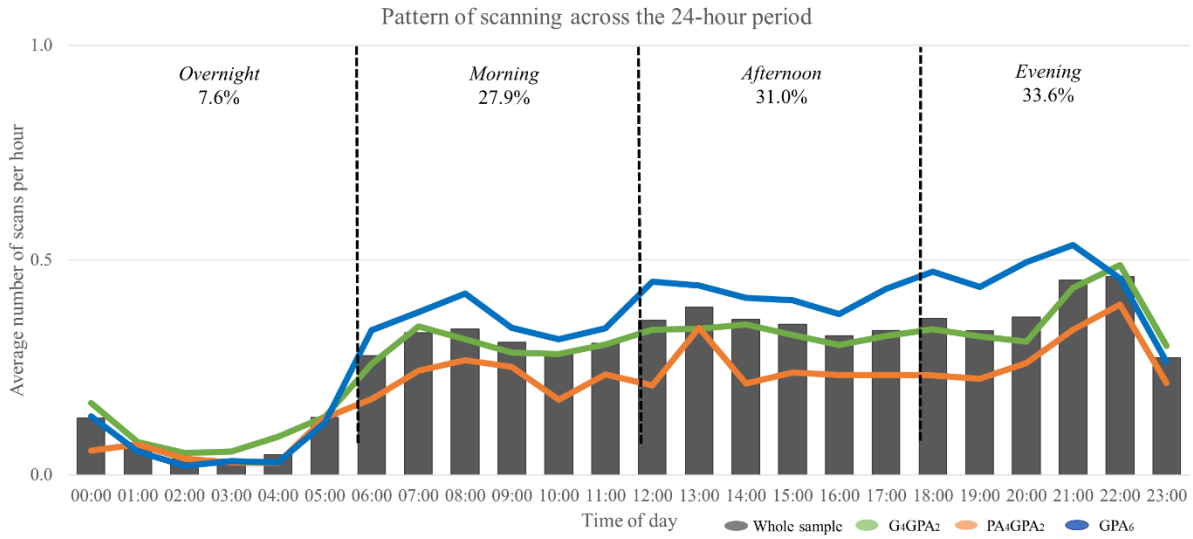

Figure 4.5. Scan frequency across the 24-hour period. G_4GPA_2 represents glucose feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks); PA_4GPA_2 represents physical activity feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks) and GPA_6 represents glucose and physical activity feedback (6 weeks).

In an effort to describe what information participants were presented with on the LibreLink app when they scanned the glucose sensor, the characteristics of the glucose feedback are presented in Table 4.3. Of all the scans conducted by participants during the study period (n=10,582), the majority of scans presented a *changing slowly* (i.e. '→') trend arrow (80%) and were most often in the normal range (59%). Participants saw that their glucose level was rising on 10% of scans and that their glucose was above the normal range on 36% of scans.

Participants in GPA_6 saw a significantly greater proportion of scans classified as *falling quickly* compared with PA_4GPA_2 (1% versus 0.2% of scans, p=.015). No other significant differences were observed between groups.

Table 4.3. Scan information displayed to users as a proportion (%) of total scans accumulated, reported as mean±SD

	Whole sample (n=45)	G_4GPA_2 (n=15)	PA_4GPA_2 (n=15)	GPA_6 (n=15)
Glucose Rising Quickly ↑	1.9±1.8	1.7±1.4	2.3±2.6	1.7±1
Glucose Rising ↗	8.2±3.8	8.3±3.2	7.8±5.5	8.5±2.1
Glucose Changing Slowly →	80.3±8.4	79.9±5.5	81.7±12.5	79.3±5.4
Glucose Falling ↘	5.6±2.3	6.3±1.7	4.8±2.9	5.8±1.9
Glucose Falling Quickly ↓	0.7±0.8	0.8±0.9	0.2±0.6	1±0.7*
No trend arrow	3.2±3.3	2.7±1.9	3.2±5	3.7±2.3
Above range (≥6.0 mmol/L)	36.2±14.3	38±13	36.8±16.9	33.8±13.2
Normal range (4.0-5.9 mmol/L)	59.2±12.8	56.7±9.5	59.8±16.5	61.3±11.8
Below range (<4.0 mmol/L)	4.6±6.2	5.3±7.5	3.5±6	4.9±5

*Table notes: G_4GPA_2 represents glucose feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks); PA_4GPA_2 represents physical activity feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks) and GPA_6 represents glucose and physical activity feedback (6 weeks). *, significant difference between PA_4GPA_6 and GPA_6 (p=.015).*

Freestyle Libre – app usage

To see whether participant engagement reduced over time, it was reported that time spent on the LibreLink app decreased over the six weeks among participants who had access to glucose feedback throughout the whole intervention. G_4GPA_2 and GPA_6, on average, reduced their time spent on the LibreLink app from 20.2±20 min/day in week 1 to 9.4±14.6min/day in week 6 (p=.007). When comparing these two groups, it was noted that G_4GPA_2 spent significantly more time on the LibreLink app than GPA_6 over the six weeks (16.1±11.9 versus 8.4±8.7min/day, p=.026).

Fitbit – app usage

The amount of time spent on the Fitbit app decreased significantly over the six weeks among participants that had access to feedback for the whole intervention (7.1±3.8min/day in week 1 to 3.8±2.9min/day in week 6, p=.003). However, the average amount of time spent on the Fitbit app did not significantly differ between PA_4GPA_2 and GPA_6 (14.8±11.3 versus 5.2±3.1min/day, respectively, p=.468).

Fitbit – syncs

Despite participants spending less time on the Fitbit app, the number of syncs per day did not change significantly during the intervention period (i.e. week 1: 6.9±7.8 syncs/day versus week 6: 6.5±10.2 syncs/day, p=.752) and did not differ significantly between PA_4GPA_2 and GPA_6 (11.6±12.5 versus 10.7±15.8 syncs/day, p=.098).

Fitbit – changes to default goal settings

Given that goal-setting is often incorporated in behavioural interventions, it was important to record whether participants changed the default settings. In total, 13 participants (28.9%) changed at least one of the five physical activity goals on the Fitbit app (daily step count, kcal burnt, distance, active minutes or floors). Within the specific groups, G_4GPA_2 altered steps (n=3, 20%), calories (n=3, 20%), distance (n=2, 13.3%), active minutes (n=2, 13.3%) and number of floors (n=3, 20%). Steps were increased from 10,000 to 11,500 and 15,000 and reduced to 6,000, active minutes were increased from 30 to 40 min and reduced to 20 min and floors increased from 10 to 15 and 25 and reduced to 5 and 1 per day. In PA_4GPA_2, only steps (n=3, 20%) and active minutes (n=1, 6.7%) were changed; with steps reduced to 7,000, 6,000 and 3,000 whilst active minutes increased to 200 min. In GPA_6, three participants (20%) changed their steps and one participant (6.7%) changed the number of floors. Step count goal was increased to 14,000 and reduced to 8,000 steps/day whilst floors reduced from 10 to 8 per day.

Secondary outcomes

Feasibility (practicality)

Freestyle Libre – deploying sensors

To assess the practicality of deploying the glucose sensors, the number of excess deployed monitors were examined. 157 sensors were deployed in total; 22 more than the intended number of sensors and averaging 3.5±1.4 sensors/participant. Only 17 participants (37.8%) completed the study using the minimum (expected) three sensors. In total, 16 participants (35.6%), 7 (15.6%), and 1 (2.2%) required one, two or three additional sensors, respectively. Additional sensors were required due to being faulty (29.3%) or displaced whilst worn (70.7%).

Freestyle Libre – compliance to minimum scanning requirement

Compliance to scanning data revealed that 27 participants (60%) set the LibreLink app to offer reminders to scan the glucose sensor if seven to eight hours had lapsed since the preceding scan

(via a smartphone notification). Of these individuals, only two participants (4.4%) (from G_4GPA_2) adjusted the reminder; changing it to remind them five or six hours after the preceding scan. Participant compliance to scanning was important because it impacted data capture, with missing data a key indicator of how much time lapsed before the participant scanned (Table 4.4). No significant differences in the number of missing minutes, number of missing events or data capture of glucose levels were revealed between the groups and the amount of missing data did not change significantly over the intervention.

Table 4.4. An outline of data capture from the Freestyle Libre, reported as mean±SD

	Total data capture (%)			Number of missing data events (per day)			Amount of missing data (min/day)		
	G_4GPA_2	PA_4GPA_2	GPA_6	G_4GPA_2	PA_4GPA_2	GPA_6	G_4GPA_2	PA_4GPA_2	GPA_6
Week 1	87.6±2.7		86.7±4.8	0.5±0.5		0.7±0.5	27.4±6.5		28.0±9.8
Week 2	87.4±15.7		93.7±4.5	0.6±0.6		0.8±0.7	27.1±31.7		13.0±9.2
Week 3	87.2±16.5		91.9±6.5	0.6±0.4		0.8±0.7	26.8±33.6		17.1±13.0
Week 4	82.0±21.5		91.1±9.1	0.7±0.5		0.7±0.6	37.7±44.0		18.8±18.6
Week 5	85.8±14.7	80.2±11.7	89.0±11.6	0.8±0.7	0.8±0.6	0.9±0.6	29.8±30.0	41.6±23.3	22.7±23.8
Week 6	83.1±17.5	73.2±28.6	89.6±10.8	0.9±0.7	0.7±0.6	0.9±0.5	35.1±35.7	55.3±58.5	21.6±22.1

Table notes: G_4GPA_2 represents glucose feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks); PA_4GPA_2 represents physical activity feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks) and GPA_6 represents glucose and physical activity feedback (6 weeks).

At time of writing no guidance was available for the missing data threshold but to date, flash glucose monitoring is mainly purchased privately and is only in use by selected NHS patients (NICE, 2017). *In comparison, continuous glucose monitoring is also not routinely provided to people at risk, nor diagnosed with Type 1 or Type 2 diabetes* (NICE, 2015a, 2015b) *but can be in Type 1 diabetics if individuals are willing to commit to using it ≥70% of the time. 70% of the time refers to minimising missing data to <432 min/day.*

Fitbit – compliance to minimum syncing and charging requirement

To monitor participant compliance with syncing and charging the Fitbit, it was recorded that 24 participants (53.3%) did not receive any reminder email prompts to sync the Fitbit. Of the participants who received an email prompt, 12 (50%) received a single prompt whilst 5 (20.8%), 3 (12.5%), 2 (8.3%) and 2 (8.3%) received 2, 3, 4 or 5 prompts, respectively. It was noted that all participants responded because new syncs were identified after the email prompt had been sent. For Fitbit charging compliance, 35 participants (77.8%) had at least one occurrence of a battery status of 25-75% whilst nine participants (20%) recorded a battery status of <25%. Despite the need to deliver email prompts, no losses in data were recorded.

Feasibility (acceptability)

Smart phone usage tracking

All participants consented to the full coverage option for Ethica Data (all 14 data sources recorded, including app usage, GPS and screen state). However, despite consenting to having their app usage monitored, it was noted that seven participants (15.6%) had no LibreLink app usage data and nine participants (20%) had no Fitbit app usage data available.

Fitbit – wear compliance

To determine the acceptability of wearing a Fitbit, it was noted that 36 participants (80%) provided seven valid days of Fitbit data, seven participants (15.6%) provided six valid days and two participants (4.4%) provided four valid days (6.7±0.7 valid days/person). Number of valid days did not differ significantly between groups. However, on average, G_4GPA_2 wore the Fitbit significantly longer each day than PA_4GPA_2 and GPA_6 (912.4±63.3 vs. 832±61.1 vs. 851±60.7 min/day, respectively, p=.002). During the intervention period, 22 participants (48.9%) provided the full 42 days of valid Fitbit wear; averaging 40.1±3.2 valid days/person. No significant differences in the number of valid days (p=.175) nor wear time (p=.508) were observed between groups. Furthermore, wear time did not differ significantly through the intervention period (p=.245).

Behaviour Change

Despite participants gaining access to their physical activity feedback, no group differences (p=.593) nor differences over time (p=.373) were revealed for step count (Figure 4.6); therefore, step count was maintained throughout the intervention. Albeit not significant, meaningfully increases in step count were observed from the fourth to the fifth week of the

intervention for G_4GPA_2 (+1071 steps) and PA_4GPA_2 (+1214 steps) but not for GPA_6 (-12 steps). These noticeable increases reflected the point of unmasking physical activity and glucose feedback, respectively. Glucose levels also did not differ significantly between groups (5.6±0.5 versus 5.5±0.4 mmol/L, p=.719) and did not change significantly over the six weeks (from 5.6±0.7 mmol/L in week 1 to 5.5±0.6 mmol/L in week 6, p=.724).

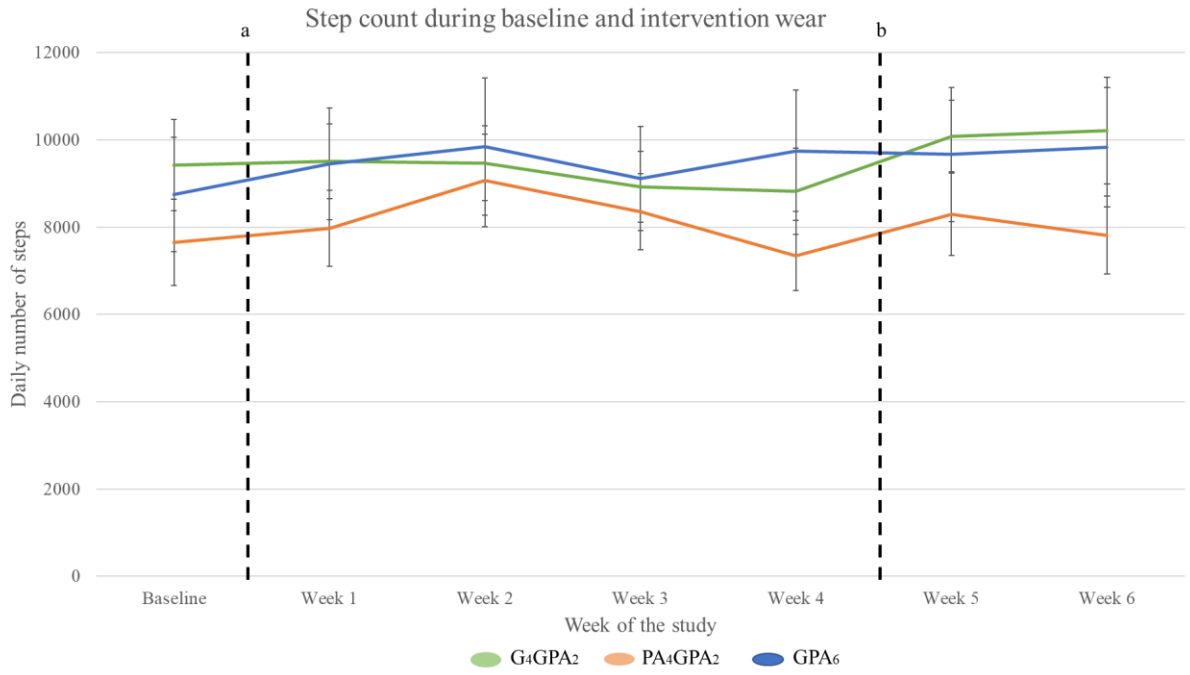

Figure 4.6. Step count from baseline to week 6 of the intervention, reported as EMM±SE. Figure notes: G_4GPA_2 represents glucose feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks); PA_4GPA_2 represents physical activity feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks) and GPA_6 represents glucose and physical activity feedback (6 weeks). Error bars represent standard error. Point of unmasking physical activity feedback occurred at (a) for PA_4GPA_2 and GPA_6 and (b) for G_4GPA_2.

Changes in technology readiness, health status and attitudes toward health

Baseline and follow-up questionnaires were completed to observe whether participants changed their technology readiness, health status and risk perception of diabetes. No significant differences between baseline and follow-up nor between groups were observed. Table 4.5 outlines key frequency data for technology readiness and perceived risk of developing diabetes questionnaires. Although not statistically significant, four fewer participants (-8.9%) were classified as *Skeptic* (high optimism, moderate innovativeness and low levels of discomfort and

insecurity) about technology in general and five more participants (+11.1%) were classified as *Pioneer* (high levels of optimism, innovativeness, discomfort and insecurity).

At baseline, to profile the health status of the sample, it was recorded that 14 participants (36.8%) reported mobility problems, two participants (5.3%) reported problems relating to self-care, nine (23.7%) reported problems performing usual activities, 25 (65.8%) reported discomfort/pain and nine (23.7%) reported problems relating to anxiety/depression. From baseline to follow-up, participants reported a similar perceived overall health score (81±13.5 versus 79.2±17.1 (out of 100), respectively, p=.340).

Table 4.5. Descriptives for questionnaire responses relating to general technology readiness and perceived risk for developing diabetes, reported as N (%).

	Whole sample (n=45)	
	Baseline	Follow up
TRI 2.0[a]		
Skeptic	17 (37.8)	13 (28.9)
Explorer	14 (31.1)	13 (28.9)
Avoider	2 (4.4)	3 (6.7)
Pioneer	2 (4.4)	7 (15.6)
Hesitator	10 (22.2)	9 (20)
RPS-DD, number of respondents who agreed		
I feel that I have little control over risks to my health	4 (8.9)	3 (6.7)
If I am going to get diabetes, there is not much I can do about it	1 (2.2)	1 (2.2)
I think that my personal efforts will help control my risks of getting diabetes	43 (95.6)	43 (95.6)
People who make a good effort to control the risks of getting diabetes are much less likely to get diabetes	44 (97.8)	41 (91.1)
I worry about getting diabetes	30 (66.7)	27 (60)
Compared to other people of my same age and sex (gender), I am less likely than they are to get diabetes	12 (26.7)	12 (26.7)
Compared to other people of my same age and sex (gender), I am less likely than they are to get a serious disease	13 (31.1)	11 (24.4)
Worrying about getting diabetes is very upsetting	15 (33.3)	16 (35.6)

[a]Skeptic: low levels of optimism, discomfort and insecurity but moderate levels of innovativeness; Explorer: high levels of optimism and innovativeness but low levels of discomfort and insecurity; Avoider: low levels of optimism and innovativeness but high levels of discomfort and insecurity; Pioneer: high levels of optimism, innovativeness, discomfort and insecurity; and Hesitator: high levels of optimism, low levels of innovativeness and moderate levels of discomfort and insecurity. Abbreviations: TRI, Technology Readiness Index; RPS-DD, Risk Perception Survey for Developing Diabetes

4.5. Discussion

Summary

The aim of the present study was to examine participant engagement with two digital health technologies presenting physical activity and glucose feedback over six weeks and observe how feasible the intervention was to implement. The primary findings revealed that participant engagement (app usage as well as glucose scan frequency) was initially high upon receiving the devices and decreased over time but was sustained above minimum levels at six weeks (i.e. above the level of 'compulsory engagement' as required), and more than a quarter of paticipants changed at least one of their physical acivity goals. That said, there were hurdles to study recruitment given the imature nature of the glucose sensing technology and companion feedback apps (i.e. need for compatible smartphone); however, this will likely be overcome in the very near future as iOS support becomes available. Despite this, the study was feasible to implement with high participant adherence to device wear, low amounts of missing data and no participants withdrew from the intervention.

User engagement

App usage with the Fitbit and LibreLink apps

In the present study, app usage was used as a proxy indicator for participant engagement. Findings demonstrated an initial flurry of interest in accessing the LibreLink and Fitbit apps (20 min/day and 7 min/day, respectively). By the final week of the intervention, participants were still spending an encouraging amount of time on the apps (9 min/day on the LibreLink app and 4 min/day on the Fitbit app). This decline in engagement over time was expected given that initial novelty of technologies can fade over time (Lazar et al., 2015). Also, reductions in app usage does not necessarily imply a reduction in engagement; instead, becoming increasingly familiar with navigating the app interface to digest feedback may have led to users becoming more efficient. Despite this, it has been shown elsewhere that apps can experience fewer than three visits per week (Flurry Analytics, 2009), that only 16% of users access a health app more than twice after downloading it (Pramis, 2013) and that 43% of users stop accessing weight-loss apps after four weeks (Laing et al., 2014). That said, our observation that participants were continuing to access both apps into the sixth week was an encouraging finding. Other particularly interesting findings were that app usage for the LibreLink app was slightly greater than Fitbit app usage (11 min/day versus 8 min/day, respectively). In the present study, Fitbit app usage may have been lower because up-to-date physical activity feedback was

also displayed on the wrist-worn device; perhaps limiting participant interest in accessing the more comprehensive (and historical) physical activity feedback on the smartphone app. Together, these findings demonstrate that objective monitoring of participant engagement provided valuable insight into how participants used the digital health technologies deployed.

Scanning and syncing frequency

In addition to a reduction in time spent on the health apps, glucose scanning frequency reduced from approximately 9 scans/day in the first week to 6 scans/day in the last week. Similarly to app usage, participant engagement may have been at its greatest at the start of the intervention period because the opportunity to receive glucose feedback was likely interesting and novel (Lazar et al., 2015). That said, it was promising to find that participants were maintaining an average daily number of scans that was double the compulsory level of engagement of three scans/day. This finding suggests that participants may have found the glucose feedback (or simply the act of scanning) to be sufficiently interesting six weeks later. However, it was surprising to observe that PA_4GPA_2 participants did not scan the glucose sensor as often as G_4GPA_2 and GPA_6 did upon the day of unmasking (3.9 versus 8.8 scans/day, respectively). This may be because PA_4GPA_2 participants became accustomed to wearing the glucose sensor over the four weeks and having to wait to access its feedback may have brought down its initial 'wow' factor, whereas G_4GPA_2 and GPA_6 had immediate access upon applying the sensor, bringing with it greater levels of engagement. In addition, the suggestion that participants scanned most often whilst in the 'target range' brings with it complexity as participants were very likely to go above/below this range. Moving forward, with increasing technological sophistication, perhaps a dynamic target range would be more suitable for all users of this technology; regardless of presence of a diabetes diagnosis. Participants tended to scan most often between 21:00-22:00, which may infer a potential key opportunity to deliver summative end-of-day feedback to users (in addition to real-time feedback).

In contrast, the frequency with which participants synced the Fitbit did not change over the six weeks (7 syncs/day). This high observed frequency of syncing was unlikely reflective of participants accessing the Fitbit app seven times per day. Instead, the author acknowledges that the automatic 'all day sync' feature may have been disenabled, either by technical error (settings reverting to default configuration) or participants adjusting the settings (via the app). Therefore, labelling number of syncs as a reliable metric of engagement is hindered by not knowing with certainty whether the sync was performed by the participant opening the app, because they were interested in their feedback, or whether it was an automatic sync. Therefore,

the present study recommends that syncing frequency may instead be better applied as a metric to monitor data transfer.

Changing physical activity goals

In the present study, participants were instructed how to change their goals via the Fitbit app and informed they could change them if they wished to (but did not have to). Interestingly, almost a third of participants in the present study decided to change at least one of five physical activity goals. Most (69%) of the participants who changed a physical activity goal changed their step count goal which may in part be because it was the primary goal displayed via device and Fitbit app. Moreover, step count is an easily understood metric, a characteristic that may partly explain why pedometers (or step counters) have an important role to play in physical activity interventions (Bravata et al., 2007). It was noted that six of the nine changes to step count were reductions. Personalising goals to be more achievable for individuals (by increasing or decreasing the target) have previously been shown to encourage greater feedback engagement (Laing et al., 2014). The author acknowledges that participants may not have personalised the goals because they had uncertainty navigating the app, were unsure of what these values should be for them, or they may have been content with the default values.

Intervention feasibility and behaviour change

Feasibility of the recruitment strategy

Given the intention of recruiting individuals at risk of developing type 2 diabetes, who have been prioritised to prevent disease onset (Bansal, 2015), it is important to assess the feasibility of the recruitment strategy implemented. The inclusion criteria revealed that only 17% of individuals who expressed an interest were eligible to take part. Almost two-thirds of interested individuals were ineligible because their level of diabetes risk was ‘low’. In addition, approximately one-fifth of adults were ineligible because they did not own a compatible Android smartphone. Despite more smartphone sales in 2017 (Statistica, 2018) and having 46% of the UK market share (Statistica, 2017), this was a significant contributor to ineligibility. The authors expect the technologies to soon be accessible on iOS and were only a concern in the present study due to the companion app being immature. The final sample revealed that only 7% were confirmed as living with prediabetes. The risk assessment tools, as employed in the present study, can identify individuals with multiple risk factors of developing type 2 diabetes. These multiple risk factors can increase an individual’s likelihood of being pre-diabetic, but may not necessarily be at that moment in time, pre-diabetic (Cowie et al., 2009). Previous

larger studies, with in excess of 3,000 participants, have identified 17.5-26.5% of screened individuals presenting impaired glucose regulation (Gray et al., 2012; Webb et al., 2011). As a result, future screening efforts are encouraged to target individuals at greatest risk of developing type 2 diabetes by also using a confirmatory HbA1c reading.

Feasibility of deploying these technologies

Given the novel approach of deploying digital health technologies to present behavioural and physiological feedback simultaneously, it was important to assess its feasibility. With all participants attending appointments and no non-usage attrition or participant withdrawals recorded, the study is deemed feasible. Data capture from the Fitbit and Freestyle Libre also demonstrated great feasibility (40 valid days of physical activity data and 80-94% glucose data capture). Previous studies have, however, demonstrated high wear compliance (more than ten hours on 95% of days) for the Fitbit (Cadmus-Bertram et al., 2015) which highlights wear-ability. An important limitation was the frequency of accidental displacement of the glucose sensors which saw only 38% of participants using three (expected) glucose sensors. Previous studies have reported mild incidences of skin irritation, bruising and bleeding in <9% of cases and were considered typical cases for medical-grade adhesives (Bailey et al., 2015; Bolinder et al., 2016). Given the resulting cost implications of providing replacements (£57.95/sensor), efforts are needed to minimise sensor displacement. Displacements in the present study may be in part because of positioning or it may be that participants forgot they were wearing the sensors because participants were very unfamiliar with wearing a glucose sensor. Given other digital health technologies are largely worn elsewhere on the body (e.g. activity monitors on the wrist similarly to watches) (Sanders et al., 2016), it is an important point to consider whether the sensor may be better positioned in a more protected location (e.g. abdomen). Overall, the present study supports the feasibility and potential of these two digital health technologies for continuous health monitoring.

Changes in physical activity and glucose

It was envisaged that the conduit through which people may reduce their risk would be via monitoring their lifestyle behaviours and the physiological consequences of those behaviours. In the present study, no significant increases in step count were observed (averaging 8589 and 9267 steps at baseline and week 6, respectively). However, despite no significant increase in step count, it is important to highlight that participants in G_4GPA_2 did increase their step count by approximately 1,000 steps upon unmasking physical activity feedback after four weeks.

Similarly, and an even more intriguing finding, was that participants in PA_4GPA_2 also increased their step count by approximately 1,000 steps upon unmasking of glucose feedback. By comparison, GPA_6 participants (i.e. those having access to both physical activity and glucose feedback throughout) had reduced their step count by 12 steps at the same week timepoint. The introduction of 'new' feedback may have driven the results of these formed mentioned participant groups; however, it may also be partially due to these participants having contact with the research team which may have reignited motivation or perhaps desire to please the researchers.

Another finding of interest was the fact that despite no guidance being offered by the research team as to when or why to scan the glucose sensor, 36% of scans were when glucose levels were above the target range. This interesting finding may suggest that participants may have had some understanding about when and why glucose levels may fluctuate (e.g. to observe the effects of dietary intake and/or physical activity or prolonged sedentary time). To help encourage this from the outset, previous studies have incorporated education to illustrate activity-related reductions in glucose to inform participants of the health benefits of physical activity (Allen et al., 2008; Bailey et al., 2016). Moving forward, it is important to consider not only how to present information but also how to facilitate understanding (Pagliari, 2007) so incorporating personalised education may be a key addition to encourage behaviour change. Moreover, such educational strategies may benefit from employing a form of gamification as a way to gradually expose users to feedback by having users complete challenges (Piwek et al., 2016).

Strengths and limitations

The strengths of this study include the use of novel, minimally-invasive digital health technologies to present feedback about physical activity and glucose levels. Deploying these two technologies in combination offered valuable insight into how individuals at moderate-to-high risk of developing type 2 diabetes engaged with the devices and apps. For the quantification of participant engagement, multiple platforms were used to objectively and remotely monitor non-usage and dropout attrition. Furthermore, using Ethica Health allowed the research team to capture participant preference toward data sources (i.e. if any of them raised concern) and permitted a dynamic consent strategy by allowing participants to remotely withdraw from the study at any time.

The limitations of the present study include not obtaining glucose levels at baseline (for any participants) and from PA_4GPA_2 participants who were masked to this feedback for the first four weeks of the intervention period. Technological restrictions meant that, despite quantifying time spent on the apps, we were unable to identify what specific features and pages were viewed on the apps. Given that participants used their personal smartphones, phone and app updates occurring during their participation restricted our confidence in gleaning insight about the frequency that participants chose to sync the Fitbit (as an indicator of engagement).

4.6. Conclusions

The present study demonstrated that adults at moderate-to-high risk of developing type 2 diabetes engaged with physical activity and glucose feedback presented by digital health technologies. Several important improvements to the study have been highlighted: (a) the need to explore the technology in individuals presenting prediabetes; (b) expand the inclusion criteria to include individuals with non-Android smartphones; (c) provide detailed instructions and/or training on how to navigate the apps; and (d) provide education sessions to help participants understand, interpret and act on the behavioural and physiological feedback presented by the digital health technologies. Overall, the findings suggest it is feasible to provide individuals with feedback on movement behaviours and the physiological consequences of those behaviours through digital health technologies in the context of type 2 diabetes prevention.

Chapter Five

General Discussion

5.1. Summary

The present thesis is comprised of three studies which contribute to research on physical activity and health feedback and the use of digital health technologies in the prevention of chronic diseases, particularly type 2 diabetes. The overall purpose of the thesis was to investigate the associations between brain activation and personalised feedback and to determine whether coupled feedback presented by digital health technologies could influence behaviour change in an at-risk population.

Firstly, a systematic review was conducted in Study One to identify studies that used functional magnetic resonance imaging (fMRI) to assess how people's brains responded to health messages pertaining to key lifestyle behaviour risk factors for chronic diseases; namely, physical inactivity, sedentary behaviour, smoking, diet and alcohol consumption. Hereon Study One is referred to as the *systematic review*. Having identified that only one study had investigated brain responses to physical activity or sedentary behaviour information, Study Two assessed the neural responses of adults when they were presented with personalised feedback relating to movement behaviours (physical activity, sedentary behaviour) whilst inside an MRI scanner. In addition, individuals were presented feedback relating to the physiological consequence of these behaviours (glucose) to align with our interest of moving toward providing coupled feedback. Study Two found that the glucose health messages resulted in a greater neural response in the prefrontal cortex compared with the behavioural health messages, providing support for an intervention incorporating physiological feedback in addition to behavioural feedback. Hereon Study Two is referred to as the *brain activation pilot study*. Therefore, Study Three was a randomised feasibility trial investigating participant engagement with digital health technologies that presented personalised behavioural and physiological feedback to individuals living with moderate-to-high risk of developing type 2 diabetes. Results showed that it was feasible to conduct an intervention offering both behavioural and physiological feedback through digital health technologies and participants engaged with the feedback over the six weeks. Hereon Study Three is referred to as the *feasibility intervention*. Overall, this thesis has shown that lifestyle interventions deploying digital health technologies presenting physiological and behavioural feedback have potential to enhance participant engagement, which is an essential step in successful and prolonged behaviour change.

5.2. Key discussion points

5.2.1 Health messaging: Can we learn from smoking cessation?

Having identified in the systematic review that a large amount of the health messaging fMRI literature focuses on smoking cessation, there is a need to consider whether the lessons learnt can be applied to other behaviours, including physical activity. Having said that, it must be clearly acknowledged that these behaviours require individuals to make very different decisions. As a brief example, individuals should 'stop' smoking but 'do' activity. If a person intends to stop smoking, they can be referred to stop smoking services and are encouraged to undergo nicotine replacement therapy during the initial 8-12 weeks (NHS Choices, 2016). To reduce the chance of relapse, individuals are offered weekly face-to-face (or telephone) contacts for the initial four weeks then less frequent contacts in the subsequent eight weeks with regular carbon monoxide readings conducted to monitor adherence (NHS Choices, 2016). It remains unclear what an effective equivalent may be for individuals at risk of developing type 2 diabetes. As a similar lifestyle related disease, the same support should be given to individuals who wish to become more physically active. Even though physical activity promotion has largely been unsuccessful with the majority of the population obtaining insufficient levels of physical activity (Chaudhury et al., 2008), perhaps the information provided has not been potent enough to initiate behaviour change. The findings presented in this thesis suggest that the provision of feedback demonstrating the physiological consequence of movement behaviours (e.g. glucose levels) are encouraging but it is still early days for the application of changing behaviour.

The brain activation pilot study identified that fMRI can be used to quantify people's response to personalised health messages. Having also highlighted that fMRI may not be the most practical or feasible tool to capture naturalistic exposure to feedback presented by digital health technologies, further lessons may be learnt from the smoking cessation literature. For instance, much of the smoking cessation literature has explored the presentation of threatening messages to motivate people to refrain from smoking. This has in part been substantiated by studies using eye-tracking technology which quantifies visual attention and is likely a more practical neuroimaging tool to use. Findings have revealed that the addition of graphic warning labels to cigarette packages, which demonstrate the negative health consequences of smoking, are often met with 'defensive avoidance' but they can promote better recall of the health risks (Kessels et al., 2010; Strasser et al., 2012). Similar research has also investigated visual attention to food

and beverage advertising (Velazquez & Pasch, 2014) as well as beer and cigarette advertising (Krugman et al., 1994). Therefore, it may be worthwhile exploring whether eye tracking can be applied within the context of physical activity health messages. For instance, eye-tracking technology may allow us to objectively monitor overt visual attention to feedback delivered via wearable technologies and their companion smartphone apps. This may help us better understand users and their varying, complex patterns of use that cannot be gleaned from self-report measures or fMRI alone.

5.2.2 Education on the stimulus-response relationship between physical activity and glucose: A key ingredient?

Despite growing evidence for the stimulus-response between physical activity and glucose levels in individuals living with and without diabetes (Buckley et al., 2014; Dunstan et al., 2012; Fritschi et al., 2016; Healy et al., 2008; Henson et al., 2013; Thorp et al., 2010), only a couple of studies (to the authors knowledge) have capitalised on this relationship as an educational tool to demonstrate the health benefits of physical activity (Allen et al., 2008; Bailey et al., 2016). Allen and colleagues presented 'personal' and 'role model' glucose graphs to individuals living with diabetes which depicted activity-related reductions in glucose (Allen et al., 2008). Findings revealed a 5 min/day increase in moderate-intensity physical activity at the expense of sedentary time. In addition, Bailey and colleagues taught individuals living with prediabetes how to set goals, monitor their exercise and glucose levels, and how to observe their interaction using continuous glucose monitoring; improving adherence to a home-based exercise programme (Bailey et al., 2016). Knowing how best to incorporate education into a free-living setting will be a future direction from this thesis.

The feasibility intervention investigated the use of both physiological and behavioural data and the effect they had on behaviour change in individuals at risk of type 2 diabetes. Despite sufficient engagement with the technologies, participants did not significantly increase their physical activity or reduce their sedentary behaviour which could be attributed to participants observing a stronger stimulus-response coupling between glucose and diet rather than physical activity. This study did not incorporate an education session about interpreting the feedback provided by the technologies or the stimulus-response relationship. There were also no instructions provided regarding when or why to scan the glucose sensors. Nevertheless, 36% of glucose scans occurred when glucose levels were above the target range. Whilst individuals were informed about the purpose of the study, not all would have been equipped with the

knowledge of the acute responses of glucose levels from being physically active. Incorporating an education session could therefore improve the potency of an intervention and should be tested in future study iterations.

The National Diabetes Prevention Programme (NDPP), in its current form, also focusses heavily on in-person education sessions, during which diet and physical activity are key topics. However, in-person education sessions, and particularly laboratory-based education sessions, can be costly and require people to travel and commit time. It may be that as digital health technologies integrate multiple health measures within a single form (e.g. physical activity and glucose measured by the same device), education on the stimulus-response relationships may also become integrated within the technology. *Showing people* via feedback devices could be more effective than *telling people* why they should be more active and/or less sedentary (Latimer-Cheung et al., 2013). For example, an app which continually receives glucose levels and steps taken may be able to alert the user when they should go for a walk (e.g. if glucose reaches hyperglycaemic levels). If the user then completes the walk, the app may positively reinforce the decision by showing their glucose level returning to baseline quicker than if they had remained seated (e.g. *"Well done, by going for that walk your glucose returned to normal 22 minutes quicker than if you had remained sat down. Walking on most days will reduce your risk of developing diabetes by 8%"*). That said, this message may need to be framed in an alternate way to capture the attention of other individuals; therefore, it is important to try and have flexibility in how messages are presented so that individuals can resonate and feel competent to act on the information shown. However, until technology enables this concept to be tested, in-person education sessions on stimulus-response relationships followed by free-living exposure to behavioural and physiological feedback seems to be the next step on the journey of digital health technologies to elicit sustained increases in physical activity.

5.2.3 Targeting the right people for interventions

Given the high prevalence of multiple negative lifestyle behaviours in today's society, such as 'hyper-sitting syndrome' (Gray, 2016), and with 5-10% of adults developing diabetes (Bansal, 2015), it is vital to target the right people. Objectively measuring how people engage with digital health technologies, as done in the feasibility intervention, may help to identify individuals most suitable for these types of interventions and who may require greater levels of support (Serrano et al., 2017). It is not only *what* education support is needed but also the type and level (i.e. some may need more support than others). The feasibility intervention revealed variations in the level of engagement between participants, which may suggest that

some were more engaged with technology than others. It may also be that some people were able to access and interpret information quicker than others. By stratifying individuals who might benefit from diabetes prevention interventions by the level of support or education they require, future interventions may better optimise resources to give participants an equal chance of making positive lifestyle changes such as increasing their physical activity.

It is important for type 2 diabetes prevention interventions to target those who would benefit most from lifestyle changes; given that 592 million individuals are likely to be diagnosed by 2035 (Chapman & Elstein, 1995) and prediabetes burdening more than one-third of adults in England (Green et al., 1996). That said, targeting individuals who need support will be crucial to ensure effective allocation of available resources. The feasibility intervention recruited 45 individuals living at moderate-to-high risk of developing type 2 diabetes from the community within a four-month period. Screening individuals from the community is important given that many people (e.g. low income, unemployed and less well educated) do not attend NHS health checks and thus do not have up-to-date medical records (Dryden et al., 2012). However, community-based recruitment comes with its own challenges that must be overcome before such strategies are implemented. Firstly, despite screening as moderate-to-high risk, only 7% of participants in the feasibility intervention had prediabetes. Similar to the limitations of other screening initiatives, the one used in this thesis identified individuals who presented multiple risk factors but this can only be suggestive of prediabetes (Patel et al., 2015). Targeting individuals living with prediabetes has been declared a priority for diabetes prevention efforts (Barry et al., 2017). Previous studies in the UK have been able to identify prediabetes in 17.5-26.5% of screened individuals using GP practice databases (Gray et al., 2012; Webb et al., 2011). Consequently, efforts to improve the way in which individuals with undiagnosed prediabetes are identified, particularly in community settings, are needed. Difficulties recruiting from community settings are also highlighted by our finding that almost two-thirds of individuals interested in taking part in the feasibility intervention were ineligible because their level of diabetes risk was too low. Also, as previously highlighted, current technological limitations may provide significant barriers to reaching people in need of interventions, as one-in-five individuals were ineligible for the feasibility intervention because they did not own or use a compatible smartphone. With 7.8 million individuals in the UK identified as non-users of the internet (Good Things Foundation & Yates, 2017) and 24% of adults not using a smartphone (Ofcom, 2017), ensuring that interventions are not too technologically restrictive is important.

5.2.4 Digital health technologies: Ready for real-time but are they ready for prime-time?

The prevalence of digital health technologies (and their companion smartphone apps) has continued to grow over the last decade (Research2Guidance, 2017). With an estimated 2.3 billion smartphone users (Statistica, 2018) and smartwatch ownership increasing in the UK from 5% in 2016 to 9% in 2017 (Ofcom, 2017), digital health technologies appear to be here to stay. More specifically, the growing marketplace for health-related apps (Research2Guidance, 2017) has brought with it increases in smartphone ownership and improvements in app quality (Research2Guidance, 2016). These statistics are quite compelling, but they do not necessarily mean that digital health technologies will be the answer to chronic disease burden. Devices often become unused items 'left in a sock drawer' never to be used again. Previous work has found that 65% of users abandon Fitbit devices within two weeks (Shih et al., 2015), 43% of people no longer access MyFitnessPal apps after one month (Laing et al., 2014) and 33% of American users no longer use their activity monitor within six months of purchase (Ledger et al., 2014). Indeed, some individuals do not use the technology for its intended purpose (Kelders et al., 2012). In comparison, the feasibility intervention observed a reduction in time spent on the LibreLink and Fitbit apps (20 min/day and 7 min/day reducing to 9 min/day and 4 min/day, respectively over six weeks) and participants complied well with wearing and scanning the minimally-invasive glucose sensor for six weeks (80-94% data capture). However, a problem with this glucose sensor was that 62% of participants required additional sensors, resulting in a higher than expected cost per participant, predominantly because these sensors were accidentally displaced. Therefore, it is unlikely that such technologies, in their current form, will be incorporated into routine clinical services if they need to be frequently replaced or if patients do not engage with them sufficiently to evoke the required health improvements. That said, future iterations of these technologies will likely evolve with greater, more enhanced functionality. Therefore, efforts to sustain user interest in digital health technologies are needed.

This thesis provides evidence for the potential of providing behavioural feedback with physiological feedback to help sustain use and engagement with the digital health technologies. It is perhaps the increased functionality of the technologies that delays this 'sock drawer effect'. In the feasibility intervention, participants wore both the Fitbit and Freestyle Libre for the full six weeks and maintained engagement above the 'minimum ask'; scanning the Freestyle Libre at least twice as often as they were asked to. However, the digital health technologies used in

this thesis have important limitations that should be overcome before they can be deemed ready for prime-time. Two wearable technologies were needed (one for behavioural feedback and one for physiological feedback), each worn in a different location, with a different attachment mechanism, different charging requirements, different memory storage capabilities and different apps. To provide truly combined behavioural and physiological feedback, this information must be harmonised within a single digital health technology/app. There are also more short-term problems, with recruitment to the feasibility intervention restricted to users of certain Android smart phones; leading to approximately one-fifth of screened adults being ineligible for the study. Whilst the Abbott Freestyle Libre is likely soon accessible via iOS smartphones given other devices (e.g. Dexcom G5) are already available on both smartphone operating systems, these issues will greatly hinder the potential for such technologies to gain mass adoption. However, this should not deter investigations into the utility of these technologies to facilitate the adoption of healthier lifestyles, including increasing physical activity. Digital health technologies will continue to improve by solving the problems of previous generations and explore the integration of multiple health measures within a single wearable module. For example, Medtronic, a major competitor to Abbott, issued a press release in 2017 that eluded to a collaboration with Fitbit to integrate glucose and physical activity data via their smartphone app (Medtronic, 2017). Multi-functional apps are likely to continue advancing in the coming years. Therefore, whilst prime-time in the sense of implementation into clinical pathways may still be on the horizon, the digital technologies are making promising strides. For now, it is important to ensure that the health messages provided by these digital health technologies are effective (Driver, 2016).

5.2.5 Finding a suitable home for digital health technologies for type 2 diabetes prevention

An existing prevention programme in England refers individuals identified via GP databases or NHS health checks to a nine-month educational programme. Forming part of the Five Year Forward Plan (NHS England, 2014), the NDPP delivers a structured lifestyle intervention. Between June 2016 and March 2017, the programme had over 43,000 referrals (4,000 in the East Midlands) (Barron et al., 2017) which exceeded expectations set by the expert reference group (NHS England, 2016). However, preliminary findings suggest that only 49% of those referred attended the initial assessment (ranging from 16-86% across England) (Barron et al., 2017). The NDPP has begun to pilot the use of digital health technologies in the form of weighing scales, activity monitors and online counselling (NHS Digital, 2017). This is a

promising development and aligns well with the present thesis which supports the use of digital health technologies presenting personalised feedback in the context of diabetes prevention.

As interventions such as the NDPP increasingly incorporate digital health technologies and with the ongoing expansion of NHS Digital, efforts to widen digital participation are ongoing. For example, the NHS Digital 'Widen Digital Participation programme' aims to offer individuals skills to better manage their condition (NHS Digital, 2016b). Digital technologies offer great potential in improving the delivery and reach of healthcare (Michie et al., 2017) and with the ongoing growth of NHS Digital, the NHS seeks to maximise the integration of digital solutions within patient healthcare. Consequently, the present thesis helps inform how personalised behavioural and physiological feedback can be deployed for the prevention of chronic disease.

5.3. Challenges and potential in this area of research

5.3.1 Challenges

In addition to the challenges already mentioned, the following section acknowledges further challenges faced in this area of research. A major challenge facing researchers is that digital health technologies are regularly superseded in the consumer marketplace. Within the present thesis, both the Lumoback and Fitbit Charge 2 have been superseded since their deployment in the brain activation pilot and feasibility intervention, respectively, by the Lumo Lift and Fitbit Alta and Ionic, respectively. This is due to the increasing consumer demand for more sophisticated functionality and design (Sanders et al., 2016). In addition, the flash glucose monitor used in the brain activation pilot and feasibility intervention was deployed soon after market release in 2016. Consequently, the device did not permit masked measurement of glucose levels, so participants had to have access to feedback to capture data. Previous studies, which have been financially supported by Abbott, have had access to the Pro model which has a masked (logging) mode (e.g. Bolinder et al., 2016). Increasing competition in the physiological sensors market will likely bolster efforts to become more amenable to research applications, until then slight adjustments to devices will be actioned to fit within protocols.

A major challenge to utilising interstitial glucose sensors is the invasiveness of the devices. Despite being marketed as minimally-invasive, individuals not accustomed to these devices may not be comfortable applying and wearing these devices during routine wear. As a result, advancing technologies are exploring the potential for wireless, wearable photoplethysmography sensors to monitor physiological markers such as blood pressure

(Zhang et al., 2016) to replicate how heart rate is currently recorded via Fitbit. Other options are to follow the progression of microneedle patches placed directly on the skin (e.g. SugarBEAT, expected early 2018 and offers 24-hour wear per patch applied). Another factor that links with this notion is that interstitial glucose levels may not clearly show the physiological effect of movement behaviour when compared with traces captured using venous blood glucose samples. This is a challenge given the emphasis on using off-the-shelf technologies (i.e. continuous/flash glucose monitors, which monitor interstitial glucose levels) to try and demonstrate the effect that movement behaviours have on glucose during routine wear. Efforts are needed to increase the wear-ability of these physiological monitoring devices as well as fine-tune the signals to help reduce the medical stigma attached and improve their resonance in this space, respectively.

Other key limitations to this thesis include the convenience sampling method for the brain activation pilot and the relatively small sample size for the intervention, albeit having a feasibility focus. In the brain activation pilot, convenience sampling resulted in participants being highly educated, reporting mostly as White British, generally physically active and normoglycemic. Ideally, we would have recruited people at greater risk of developing type 2 diabetes (i.e. living with prediabetes) for the feasibility intervention. This would improve the generalisability of the study findings to the specific population of interest (Blair & Zinkhan, 2016).

5.3.2 Potential

In addition to the potential already discussed, this thesis highlights the need for future research studies to utilise sophisticated, objective measurement and intervention tools. The next iteration of this work will need to wrestle with the timing, content and composition of the coupled feedback. Being able to provide temporally sensitive cues (e.g. nudge users after sitting for too long) via feedback would keep cognitive load low (Hargreaves et al., 2010) and help overcome the notion that individuals are often disassociated with the long-term implications of immediate decisions (Critchfield et al., 2001). Presenting coupled feedback may act as a potent nudge for individuals because they will see the acute physiological consequence of their movement behaviour. This thesis has shown that the devices in isolation show promise and are acceptable from a research study perspective. However, it is acknowledged that participants may feel obligated to comply with research study protocols (i.e. have greater wear adherence) whereas user interest in the ‘real world’ (i.e. opting or choosing to wear devices) will likely vary. To ensure long-term success, investigations into the ability of the technologies to be worn

continuously as a wearable lifestyle device and used as a tool to encourage self-management of health, need to be explored. Technologies monitoring both behaviour and physiological consequence of movement behaviours may, in turn, become more mainstream. As a result, their potential use is great and, with increased integration into pre-clinical programmes (e.g. the NDPP), these efforts may contribute to alleviating burden on the NHS.

5.4. Future directions

This section outlines several recommendations for future work informed by the limitations experienced and potentials noted in this thesis, as follows:

- Strategies to sustain user interest in digital health technologies for chronic disease prevention.
- Advocate and work with device manufacturers to integrate and harmonise behavioural feedback and the physiological consequence of behaviours into a single platform/module.
- Identify the specific components of health messages and feedback provided by digital health technologies that are most effective for sustained behaviour change.
- Elucidate the key ingredients in education sessions to increase physical activity.
- Optimise stratification approaches to target those individuals in most need of interventions to prevent or delay the development of chronic diseases.
- Examine the impact of providing individuals with coupled behavioural and physiological feedback through digital health technologies within existing large-scale interventions such as the NHS National Diabetes Prevention Programme.

5.5. Overall conclusions

Interventions to prevent type 2 diabetes are urgently needed. Despite the abundance of evidence supporting the health benefits of physical activity, population levels are still critically low. To date, interventions have focussed on lifestyle behaviours, such as increasing physical activity, but advancements in technology now allow individuals to see the physiological consequences of these behaviours; information that may yield sustained behaviour change. The present thesis highlighted the utility of examining brain activations in response to personalised physiological and behavioural feedback and observed that individuals at moderate-to-high risk of developing type 2 diabetes engaged highly with coupled feedback. This work supports future research providing objective feedback on movement behaviours and the physiological consequences of these behaviours in the context of chronic disease prevention.

References

Aadland, E., & Ylvisåker, E. (2015). Reliability of the Actigraph GT3X+ accelerometer in adults under free-living conditions. *PLoS One*, *10*(8), e0134606.

Aguilar, M., Bhuket, T., Torres, S., Liu, B., & Wong, R. J. (2015). Prevalence of the Metabolic Syndrome in the United States, 2003-2012. *JAMA*, *313*(19), 1973.

Aguirre, G. K., Zarahn, E., & D'esposito, M. (1998). The variability of human, BOLD hemodynamic responses. *NeuroImage*, *8*(4), 360–369.

Ainsworth, B. E., Haskell, W. L., Herrmann, S. D., Meckes, N., Bassett Jr, D. R., Tudor-Locke, C., Greer, J. L., Vezina, J., Whitt-Glover, M. C., & Leon, A. S. (2011). 2011 Compendium of Physical Activities: a second update of codes and MET values. *Medicine and Science in Sports and Exercise*, *43*(8), 1575–1581.

Aitken, M. (2015). Patient Adoption of mHealth: IMS Institute for Healthcare Informatics. Retrieved from http://www.imshealth.com/files/web/IMSH Institute/Reports/Patient Adoption of mHealth/IIHI_Patient_Adoption_of_mHealth.pdf

Alkhaldi, G., Hamilton, F. L., Lau, R., Webster, R., Michie, S., & Murray, E. (2016). The Effectiveness of Prompts to Promote Engagement With Digital Interventions: A Systematic Review. *Journal of Medical Internet Research*, *18*(1), e6.

Allen, L. N., & Feigl, A. B. (2017). What's in a name? A call to reframe non-communicable diseases. *The Lancet. Global Health*, *5*(2), e129–e130.

Allen, N. A., Fain, J. A., Braun, B., & Chipkin, S. R. (2008). Continuous glucose monitoring counseling improves physical activity behaviors of individuals with type 2 diabetes: A randomized clinical trial. *Diabetes Research and Clinical Practice*, *80*(3), 371–379.

Allen, N. A., Fain, J. A., Braun, B., & Chipkin, S. R. (2009). Continuous glucose monitoring in non–insulin-using individuals with type 2 diabetes: acceptability, feasibility, and teaching opportunities. *Diabetes Technology & Therapeutics*, *11*(3), 151–158.

Allender, S., Foster, C., Scarborough, P., & Rayner, M. (2007). The burden of physical activity-related ill health in the UK. *Journal of Epidemiology and Community Health*, *61*(4), 344–348.

Allet, L., Knols, R. H., Shirato, K., & Bruin, E. D. de. (2010). Wearable systems for monitoring mobility-related activities in chronic disease: a systematic review. *Sensors*, *10*(10), 9026–9052.

Alley, S., Schoeppe, S., Guertler, D., Jennings, C., Duncan, M. J., & Vandelanotte, C. (2016). Interest and preferences for using advanced physical activity tracking devices: results of a national cross-sectional survey. *BMJ Open*, *6*(7), e011243-2016–011243.

American Diabetes Association. (1994). Self-monitoring of blood glucose. *Diabetes Care*, *17*(1), 81–86.

American Diabetes Association. (2010). Diagnosis and classification of diabetes mellitus. *Diabetes Care*, *33 Suppl 1*, S62-9.

American Diabetes Association. (2015a). (2) Classification and diagnosis of diabetes. *Diabetes Care*, *38 Suppl*, S8–S16.

American Diabetes Association. (2015b). Standards of Medical Care in Diabetes. *The Journal of Clinical and Applied Standards of Medical Care in Diabetes*, *38*(1).

Ammerman, A. S., Lindquist, C. H., Lohr, K. N., & Hersey, J. (2002). The efficacy of behavioral interventions to modify dietary fat and fruit and vegetable intake: a review of

the evidence. *Preventive Medicine*, *35*(1), 25–41.

Appelboom, G., Yang, A. H., Christophe, B. R., Bruce, E. M., Slomian, J., Bruyère, O., Bruce, S. S., Zacharia, B. E., Reginster, J.-Y., & Connolly, E. S. (2014). The promise of wearable activity sensors to define patient recovery. *Journal of Clinical Neuroscience*, *21*(7), 1089–1093.

Atkin, A. J., Gorely, T., Clemes, S. A., Yates, T., Edwardson, C., Brage, S., Salmon, J., Marshall, S. J., & Biddle, S. J. (2012). Methods of Measurement in epidemiology: sedentary Behaviour. *International Journal of Epidemiology*, *41*(5), 1460–1471.

Aue, T., Lavelle, L. A., & Cacioppo, J. T. (2009). Great expectations: what can fMRI research tell us about psychological phenomena? *International Journal of Psychophysiology*, *73*(1), 10–16.

Bailey, K. J., Little, J. P., & Jung, M. E. (2016). Self-Monitoring Using Continuous Glucose Monitors with Real-Time Feedback Improves Exercise Adherence in Individuals with Impaired Blood Glucose: A Pilot Study. *Diabetes Technology & Therapeutics*, *18*(3), 185–193.

Bailey, T., Bode, B. W., Christiansen, M. P., Klaff, L. J., & Alva, S. (2015). The performance and usability of a factory-calibrated flash glucose monitoring system. *Diabetes Technology & Therapeutics*, *17*(11), 787–794.

Baker, T. B., Gustafson, D. H., & Shah, D. (2014). How can research keep up with eHealth? Ten strategies for increasing the timeliness and usefulness of eHealth research. *Journal of Medical Internet Research*, *16*(2), e36.

Bandettini, P. A. (1993). MRI studies of brain activation: Dynamic characteristics. *Functional MRI of the Brain*, 144–151.

Bansal, N. (2015). Prediabetes diagnosis and treatment: A review. *World Journal of Diabetes*, *6*(2), 296–303.

Barron, E., Clark, R., Hewings, R., Smith, J., & Valabhji, J. (2017). Progress of the Healthier You: NHS Diabetes Prevention Programme: referrals, uptake and participant characteristics. *Diabetic Medicine*.

Barry, E., Roberts, S., Oke, J., Vijayaraghavan, S., Normansell, R., & Greenhalgh, T. (2017). Efficacy and effectiveness of screen and treat policies in prevention of type 2 diabetes: systematic review and meta-analysis of screening tests and interventions. *BMJ (Clinical Research Ed.)*, *356*, i6538.

Barry, M. M., D'Eath, M., & Sixsmith, J. (2013). Interventions for improving population health literacy: insights from a rapid review of the evidence. *Journal of Health Communication*, *18*(12), 1507–1522.

Barwais, F. A., Cuddihy, T. F., & Tomson, L. M. (2013). Physical activity, sedentary behavior and total wellness changes among sedentary adults: a 4-week randomized controlled trial. *Health and Quality of Life Outcomes*, *11*(1), 183.

Bassett Jr, D. R., John, D., Conger, S. A., Rider, B. C., Passmore, R. M., & Clark, J. M. (2014). Detection of lying down, sitting, standing, and stepping using two activPAL monitors. *Medicine and Science in Sports and Exercise*, *46*(10), 2025–2029.

Battersby, M., Von Korff, M., Schaefer, J., Davis, C., Ludman, E., Greene, S. M., Parkerton, M., & Wagner, E. H. (2010). Twelve evidence-based principles for implementing self-management support in primary care. *The Joint Commission Journal on Quality and*

Patient Safety, *36*(12), 561–570.

Battram, D. S., Beynon, C., & He, M. (2011). The reliability and validity of using clothing size as a proxy for waist circumference measurement in adults. *Applied Physiology, Nutrition, and Metabolism*, *36*(2), 183–190.

Bauer, U. E., Briss, P. A., Goodman, R. A., & Bowman, B. A. (2014). Prevention of chronic disease in the 21st century: elimination of the leading preventable causes of premature death and disability in the USA. *The Lancet*, *384*(9937), 45–52.

Bauman, A., Pedišić, Ž., & Bragg, K. (2016). Objective Measurement in Physical Activity Surveillance: Present Role and Future Potential (pp. 347–367). Springer, Cham.

Bauman, A., Smith, B. J., Maibach, E. W., & Reger-Nash, B. (2006). Evaluation of mass media campaigns for physical activity. *Evaluation and Program Planning*, *29*(3), 312–322.

Beaglehole, R., Bonita, R., Horton, R., Adams, C., Alleyne, G., Asaria, P., Baugh, V., Bekedam, H., Billo, N., & Casswell, S. (2011). Priority actions for the non-communicable disease crisis. *The Lancet*, *377*(9775), 1438–1447.

Beaglehole, R., & Yach, D. (2003). Globalisation and the prevention and control of non-communicable disease: the neglected chronic diseases of adults. *The Lancet*, *362*(9387), 903–908.

Beagley, J., Guariguata, L., Weil, C., & Motala, A. A. (2014). Global estimates of undiagnosed diabetes in adults. *Diabetes Research and Clinical Practice*, *103*(2), 150–160.

Bergenstal, R. M., Ahmann, A. J., Bailey, T., Beck, R. W., Bissen, J., Buckingham, B., Deeb, L., Dolin, R. H., Garg, S. K., & Goland, R. (2013). Recommendations for standardizing glucose reporting and analysis to optimize clinical decision making in diabetes: the Ambulatory Glucose Profile (AGP).

Beunza, J. J., Martínez-González, M. Á., Ebrahim, S., Bes-Rastrollo, M., Núnez, J., Martínez, J. A., & Alonso, Á. (2007). Sedentary behaviors and the risk of incident hypertension: the SUN Cohort. *American Journal of Hypertension*, *20*(11), 1156–1162.

Bhattarai, N., Prevost, A. T., Wright, A. J., Charlton, J., Rudisill, C., & Gulliford, M. C. (2013). Effectiveness of interventions to promote healthy diet in primary care: systematic review and meta-analysis of randomised controlled trials. *BMC Public Health*, *13*(1), 1203.

Bickel, W. K., Odum, A. L., & Madden, G. J. (1999). Impulsivity and cigarette smoking: delay discounting in current, never, and ex-smokers. *Psychopharmacology*, *146*(4), 447–454.

Birnbaum, F., Lewis, D., Rosen, R. K., & Ranney, M. L. (2015). Patient engagement and the design of digital health. *Academic Emergency Medicine : Official Journal of the Society for Academic Emergency Medicine*, *22*(6), 754–756.

Blair, E., & Zinkhan, G. M. (2016). Nonresponse and Generalizability in Academic Research.

Blair, S. N. (2009). Physical inactivity: the biggest public health problem of the 21st century. *British Journal of Sports Medicine*, *43*(1), 1–2. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/19136507

Blair, S. N., Kohl, H. W., Gordon, N. F., & Paffenbarger Jr, R. S. (1992). How much physical activity is good for health? *Annual Review of Public Health*, *13*(1), 99–126.

Bolinder, J., Antuna, R., Geelhoed-Duijvestijn, P., Kröger, J., & Weitgasser, R. (2016). Novel glucose-sensing technology and hypoglycaemia in type 1 diabetes: a multicentre, non-masked, randomised controlled trial. *The Lancet*, *388*(10057), 2254–2263.

Bonander, J., & Gates, S. (2010). Public health in an era of personal health records: opportunities for innovation and new partnerships. *Journal of Medical Internet Research*, *12*(3).

Bookheimer, S. (2007). Pre-surgical language mapping with functional magnetic resonance imaging. *Neuropsychology Review*, *17*(2), 145–155.

Booth-Kewley, S., Larson, G. E., & Miyoshi, D. K. (2007). Social desirability effects on computerized and paper-and-pencil questionnaires. *Computers in Human Behavior*, *23*(1), 463–477.

Bouchard, C., Shephard, R. J., & Stephens, T. (1993). *Physical activity, fitness, and health*. Human Kinetics Publishers.

Bowen, D. J., Kreuter, M., Spring, B., Cofta-Woerpel, L., Linnan, L., Weiner, D., Bakken, S., Kaplan, C. P., Squiers, L., & Fabrizio, C. (2009). How we design feasibility studies. *American Journal of Preventive Medicine*, *36*(5), 452–457.

Bravata, D. M., Smith-Spangler, C., Sundaram, V., Gienger, A. L., Lin, N., Lewis, R., Stave, C. D., Olkin, I., & Sirard, J. R. (2007). Using pedometers to increase physical activity and improve health: a systematic review. *Jama*, *298*(19), 2296–2304.

Bridgeman, B. (1992). Conscious vs Unconscious Processes The Case of Vision. *Theory & Psychology*, *2*(1), 73–88.

Brindal, E., Freyne, J., Saunders, I., Berkovsky, S., Smith, G., & Noakes, M. (2012). Features predicting weight loss in overweight or obese participants in a web-based intervention: randomized trial. *Journal of Medical Internet Research*, *14*(6), e173.

British Heart Foundation. (2017). Physical Inactivity and Sedentary Behaviour Report 2017. Retrieved from https://www.bhf.org.uk/publications/statistics/physical-inactivity-report-2017

Brug, J., Steenhuis, I., van Assema, P., & de Vries, H. (1996). The impact of a computer-tailored nutrition intervention. *Preventive Medicine*, *25*(3), 236–242.

Buckley, J. P., Mellor, D. D., Morris, M., & Joseph, F. (2014). Standing-based office work shows encouraging signs of attenuating post-prandial glycaemic excursion. *Occupational and Environmental Medicine*, *71*(2), 109–11.

Buman, M. P., Winkler, E. A. H., Kurka, J. M., Hekler, E. B., Baldwin, C. M., Owen, N., Ainsworth, B. E., Healy, G. N., & Gardiner, P. A. (2014). Reallocating Time to Sleep, Sedentary Behaviors, or Active Behaviors: Associations With Cardiovascular Disease Risk Biomarkers, NHANES 2005–2006. *American Journal of Epidemiology*, *179*(3), 323–334.

Burstein, R., Polychronakos, C., Toews, C. J., MacDougall, J. D., Guyda, H. J., & Posner, B. I. (1985). Acute reversal of the enhanced insulin action in trained athletes. Association with insulin receptor changes. *Diabetes*, *34*(8), 756–760.

Cacioppo, J. T. (2002). Social neuroscience: understanding the pieces fosters understanding the whole and vice versa. *American Psychologist*, *57*(11), 819.

Cadmus-Bertram, L. A., Marcus, B. H., Patterson, R. E., Parker, B. A., & Morey, B. L. (2015). Randomized trial of a Fitbit-based physical activity intervention for women. *American Journal of Preventive Medicine*, *49*(3), 414–418.

Cadmus-Bertram, L., Marcus, B. H., Patterson, R. E., Parker, B. A., & Morey, B. L. (2015). Use of the Fitbit to Measure Adherence to a Physical Activity Intervention Among

Overweight or Obese, Postmenopausal Women: Self-Monitoring Trajectory During 16 Weeks. *JMIR mHealth and uHealth*, *3*(4), e96.

Calvert, G. A., & Brammer, M. J. (2012). Predicting consumer behavior: using novel mind-reading approaches. *IEEE Pulse*, *3*(3), 38–41.

Camhi, S. M., Sisson, S. B., Johnson, W. D., Katzmarzyk, P. T., & Tudor-Locke, C. (2010). Accelerometer-Determined Lifestyle Activity, Cardiovascular Disease Risk Factors and Metabolic Syndrome: 830: June 3 3: 30 PM-3: 45 PM. *Medicine & Science in Sports & Exercise*, *42*(5), 76.

Campbell, M., Fitzpatrick, R., Haines, A., Kinmonth, A. L., Sandercock, P., Spiegelhalter, D., & Tyrer, P. (2000). Framework for design and evaluation of complex interventions to improve health. *BMJ: British Medical Journal*, *321*(7262), 694.

Canadian Society for Exercise Physiology. (2004). The Canadian physical activity, fitness and lifestyle approach (3rd ed.). *Ontario: Canadian Society for Exercise Physiology*.

Canalys. (2014). 1.6 million smart bands shipped in H2 2013. Retrieved from http://www.canalys.com/newsroom/16-million-smart-bands-shipped-h2-2013

Cardinal, B. J. (2016). Toward a greater understanding of the syndemic nature of hypokinetic diseases. *Journal of Exercise Science & Fitness*, *14*(2), 54–59.

Carver, C. S., & Scheier, M. F. (1982). Control theory: A useful conceptual framework for personality–social, clinical, and health psychology. *Psychological Bulletin*, *92*(1), 111.

Cascio, C. N., Dal Cin, S., & Falk, E. B. (2013). Health communications: Predicting behavior change from the brain. In *Social neuroscience and public health* (pp. 57–71). Springer.

Case, M. A., Burwick, H. A., Volpp, K. G., & Patel, M. S. (2015). Accuracy of smartphone applications and wearable devices for tracking physical activity data. *Jama*, *313*(6), 625–626.

Caspersen, C. J., Powell, K. E., & Christenson, G. M. (1985). Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research. *Public Health Reports (Washington, D.C.: 1974)*, *100*(2), 126–131.

Cengiz, E., & Tamborlane, W. V. (2009). A tale of two compartments: interstitial versus blood glucose monitoring. *Diabetes Technology & Therapeutics*, *11*(S1), S-11-S-16.

Centers for Disease Control and Prevention. (2013). Alcohol-Related Disease Impact (ARDI) application. Retrieved from http://www.cdc.gov/ARDI

Chan, A.-W., Tetzlaff, J. M., Altman, D. G., Laupacis, A., Gøtzsche, P. C., Krleža-Jerić, K., Hróbjartsson, A., Mann, H., Dickersin, K., & Berlin, J. A. (2013). SPIRIT 2013 statement: defining standard protocol items for clinical trials. *Annals of Internal Medicine*, *158*(3), 200–207.

Chapman, G. B., & Elstein, A. S. (1995). Valuing the Future. *Medical Decision Making*, *15*(4), 373–386.

Chaudhury, M., & Esliger, D. W. (2008). Health Survey for England: Physical Activity and Fitness, *1*, 59–88. Retrieved from http://www.hscic.gov.uk/catalogue/PUB00430/heal-surv-phys-acti-fitn-eng-2008-rep-v2.pdf

Chen, K. Y., & Bassett, D. R. (2005). The technology of accelerometry-based activity monitors: current and future. *Medicine and Science in Sports and Exercise*, *37*(11), S490.

Chiauzzi, E., Rodarte, C., & DasMahapatra, P. (2015). Patient-centered activity monitoring in

the self-management of chronic health conditions. *BMC Medicine*, *13*(1), 77.

Cho, H., & Salmon, C. T. (2006). Fear appeals for individuals in different stages of change: Intended and unintended effects and implications on public health campaigns. *Health Communication*, *20*(1), 91–99.

Chu, A. H. Y., Ng, S. H. X., Tan, C. S., Win, A. M., Koh, D., & Müller-Riemenschneider, F. (2016). A systematic review and meta-analysis of workplace intervention strategies to reduce sedentary time in white-collar workers. *Obesity Reviews*, *17*(5), 467–481.

Chu, R., Tauhid, S., Glanz, B. I., Healy, B. C., Kim, G., Oommen, V. V, Khalid, F., Neema, M., & Bakshi, R. (2016). Whole Brain Volume Measured from 1.5T versus 3T MRI in Healthy Subjects and Patients with Multiple Sclerosis. *Journal of Neuroimaging*, *26*(1), 62–67.

Chua, H. F., Ho, S. S., Jasinska, A. J., Polk, T. A., Welsh, R. C., Liberzon, I., & Strecher, V. J. (2011). Self-related neural response to tailored smoking-cessation messages predicts quitting. *Nature Neuroscience*, *14*(4), 426–427.

Chua, H. F., Liberzon, I., Welsh, R. C., & Strecher, V. J. (2009). Neural correlates of message tailoring and self-relatedness in smoking cessation programming. *Biological Psychiatry*, *65*(2), 165–168.

Chua, H. F., Polk, T., Welsh, R., Liberzon, I., & Strecher, V. (2009). Neural responses to elements of a web-based smoking cessation program. *Studies in Health Technology and Informatics*, *144*, 174–178.

Clark, C. C. T., Barnes, C. M., Stratton, G., McNarry, M. A., Mackintosh, K. A., & Summers, H. D. (2017). A Review of Emerging Analytical Techniques for Objective Physical Activity Measurement in Humans. *Sports Medicine*, *47*(3), 439–447.

Collins, G. S., Mughal, S., Barnett, A. H., Fitzgerald, J., & Lloyd, C. E. (2011). Modification and validation of the Revised Diabetes Knowledge Scale. *Diabetic Medicine*, *28*(3), 306–310.

Conroy, D. E., Yang, C.-H., & Maher, J. P. (2014). Behavior Change Techniques in Top-Ranked Mobile Apps for Physical Activity. *American Journal of Preventive Medicine*, *46*(6), 649–652.

Cooper, N., Tompson, S., O'Donnell, M. B., & Emily, B. F. (2015). Brain activity in self-and value-related regions in response to online antismoking messages predicts behavior change. *Journal of Media Psychology*.

Cowie, C. C., Rust, K. F., Ford, E. S., Eberhardt, M. S., Byrd-Holt, D. D., Li, C., Williams, D. E., Gregg, E. W., Bainbridge, K. E., Saydah, S. H., & Geiss, L. S. (2009). Full accounting of diabetes and pre-diabetes in the U.S. population in 1988-1994 and 2005-2006. *Diabetes Care*, *32*(2), 287–294.

Critchfield, T. S., & Kollins, S. H. (2001). Temporal discounting: Basic research and the analysis of socially important behavior. *Journal of Applied Behavior Analysis*, *34*(1), 101–122.

Culhane, K. M., O'Connor, M., Lyons, D., & Lyons, G. M. (2005). Accelerometers in rehabilitation medicine for older adults. *Age and Ageing*, *34*(6), 556–560.

d'Esposito, M., Aguirre, G. K., Zarahn, E., Ballard, D., Shin, R. K., & Lease, J. (1998). Functional MRI studies of spatial and nonspatial working memory. *Cognitive Brain Research*, *7*(1), 1–13.

Daae, J. Z., & Boks, C. (2014). Dimensions of behaviour change. *Journal of Design Research*, *12*(3), 145.

Danaei, G., Lu, Y., Singh, G. M., Carnahan, E., Stevens, G. A., Cowan, M. J., Farzadfar, F., Lin, J. K., Finucane, M. M., & Rao, M. (2014). Cardiovascular disease, chronic kidney disease, and diabetes mortality burden of cardiometabolic risk factors from 1980 to 2010. *The Lancet Diabetes and Endocrinology*, *2*(8), 634–647.

de Camp Wilson, T., & Nisbett, R. E. (1978). The accuracy of verbal reports about the effects of stimuli on evaluations and behavior. *Social Psychology*, 118–131.

Den Ouden, H. E. M., Frith, U., Frith, C., & Blakemore, S.-J. (2005). Thinking about intentions. *NeuroImage*, *28*(4), 787–796.

Dennison, L., Morrison, L., Conway, G., & Yardley, L. (2013). Opportunities and challenges for smartphone applications in supporting health behavior change: qualitative study. *Journal of Medical Internet Research*, *15*(4), e86.

Diabetes UK. (2006). Position Statement: early identification of people with type 2 diabetes. *London: Diabetes UK*.

Dietz, N. A., Delva, J., Woolley, M. E., & Russello, L. (2008). The reach of a youth-oriented anti-tobacco media campaign on adult smokers. *Drug and Alcohol Dependence*, *93*(1), 180–184.

Ding, D., Lawson, K. D., Kolbe-Alexander, T. L., Finkelstein, E. A., Katzmarzyk, P. T., van Mechelen, W., Pratt, M., & Committee, L. P. A. S. 2 E. (2016). The economic burden of physical inactivity: a global analysis of major non-communicable diseases. *The Lancet*, *388*(10051), 1311–1324.

Dinh-Williams, L., Mendrek, A., Bourque, J., & Potvin, S. (2014). Where there's smoke, there's fire: the brain reactivity of chronic smokers when exposed to the negative value of smoking. *Progress in Neuro-Psychopharmacology & Biological Psychiatry*, *50*, 66–73.

Dinh-Williams, L., Mendrek, A., Dumais, A., Bourque, J., & Potvin, S. (2014). Executive-affective connectivity in smokers viewing anti-smoking images: an fMRI study. *Psychiatry Research*, *224*(3), 262–268.

DiPietro, L., Gribok, A., Stevens, M. S., Hamm, L. F., & Rumpler, W. (2013). Three 15-min bouts of moderate postmeal walking significantly improves 24-h glycemic control in older people at risk for impaired glucose tolerance. *Diabetes Care*, *36*(10), 3262–3268.

Do, K. T., & Galvan, A. (2015). FDA cigarette warning labels lower craving and elicit frontoinsular activation in adolescent smokers. *Social Cognitive and Affective Neuroscience*, *10*(11), 1484–1496.

Dodge, R. (1906). Recent studies in the correlation of eye movement and visual perception. *Psychological Bulletin*, *3*(3), 85.

Dodge, R., & Cline, T. S. (1901). The angle velocity of eye movements. *Psychological Review*, *8*(2), 145.

Doherty, A., Jackson, D., Hammerla, N., Plötz, T., Olivier, P., Granat, M. H., White, T., van Hees, V. T., Trenell, M. I., & Owen, C. G. (2017). Large scale population assessment of physical activity using wrist worn accelerometers: The UK Biobank Study. *PLoS One*, *12*(2), e0169649.

Dominick, G. M., Winfree, K. N., Pohlig, R. T., & Papas, M. A. (2016). Physical activity assessment between consumer-and research-grade accelerometers: a comparative study in

free-living conditions. *JMIR mHealth and uHealth*, *4*(3).

Dontje, M. L., de Groot, M., Lengton, R. R., van der Schans, C. P., & Krijnen, W. P. (2015). Measuring steps with the Fitbit activity tracker: an inter-device reliability study. *Journal of Medical Engineering & Technology*, *39*(5), 286–290.

Driscoll, K. A., & Young-Hyman, D. (2014). Use of technology when assessing adherence to diabetes self-management behaviors. *Current Diabetes Reports*, *14*(9), 1–9.

Driver, M. (2016). Access vs Privacy: getting the right balance for data-driven healthcare. *The Journal of mHealth*, *3*(3).

Dungan, K. (2000). Monitoring Technologies - Continuous Glucose Monitoring, Mobile Technology, Biomarkers of Glycemic Control. In L. J. De Groot, G. Chrousos, K. Dungan, K. R. Feingold, A. Grossman, J. M. Hershman, C. Koch, M. Korbonits, R. McLachlan, M. New, J. Purnell, R. Rebar, F. Singer, & A. Vinik (Eds.), *Endotext*. South Dartmouth (MA): MDText.com, Inc.

Dunlop, S. M., Wakefield, M., & Kashima, Y. (2008). The contribution of antismoking advertising to quitting: intra-and interpersonal processes. *Journal of Health Communication*, *13*(3), 250–266.

Dunstan, D. W., Barr, E. L., Healy, G. N., Salmon, J., Shaw, J. E., Balkau, B., Magliano, D. J., Cameron, A. J., Zimmet, P. Z., & Owen, N. (2010). Television viewing time and mortality: the Australian Diabetes, Obesity and Lifestyle Study (AusDiab). *Circulation*, *121*(3), 384–391.

Dunstan, D. W., Howard, B., Healy, G. N., & Owen, N. (2012). Too much sitting–a health hazard. *Diabetes Research and Clinical Practice*, *97*(3), 368–376.

Dunstan, D. W., Kingwell, B. A., Larsen, R., Healy, G. N., Cerin, E., Hamilton, M. T., Shaw, J. E., Bertovic, D. A., Zimmet, P. Z., Salmon, J., & others. (2012). Breaking up prolonged sitting reduces postprandial glucose and insulin responses. *Diabetes Care*, *35*(5), 976–983.

Dunstan, D. W., Salmon, J., Healy, G. N., Shaw, J. E., Jolley, D., Zimmet, P. Z., Owen, N., & Committee, A. S. (2007). Association of television viewing with fasting and 2-h postchallenge plasma glucose levels in adults without diagnosed diabetes. *Diabetes Care*, *30*(3), 516–522.

Dunstan, D. W., Salmon, J., Owen, N., Armstrong, T., Zimmet, P. Z., Welborn, T. A., Cameron, A. J., Dwyer, T., Jolley, D., & Shaw, J. E. (2005). Associations of TV viewing and physical activity with the metabolic syndrome in Australian adults. *Diabetologia*, *48*(11), 2254–2261.

Dutton, W. H., & Blank, G. (2015). Cultures on the Internet.

Duvivier, B. M. F. M., Schaper, N. C., Bremers, M. A., van Crombrugge, G., Menheere, P. P. C. A., Kars, M., & Savelberg, H. H. C. M. (2013). Minimal intensity physical activity (standing and walking) of longer duration improves insulin action and plasma lipids more than shorter periods of moderate to vigorous exercise (cycling) in sedentary subjects when energy expenditure is comparable. *PloS One*, *8*(2), e55542.

Edwardson, C. L., Winkler, E. A. H., Bodicoat, D. H., Yates, T., Davies, M. J., Dunstan, D. W., & Healy, G. N. (2016). Considerations when using the activPAL monitor in field-based research with adult populations. *Journal of Sport and Health Science*.

Eisenberg, L. (1995). The social construction of the human brain. *American Journal of*

Psychiatry, *152*(11), 1563–1575.

Ekelund, U., Steene-Johannessen, J., Brown, W. J., Fagerland, M. W., Owen, N., Powell, K. E., Bauman, A., Lee, I.-M., Series, L. P. A., & Group, L. S. B. W. (2016). Does physical activity attenuate, or even eliminate, the detrimental association of sitting time with mortality? A harmonised meta-analysis of data from more than 1 million men and women. *The Lancet*, *388*(10051), 1302–1310.

Emery, S., Kim, Y., Choi, Y. K., Szczypka, G., Wakefield, M., & Chaloupka, F. J. (2012). The effects of smoking-related television advertising on smoking and intentions to quit among adults in the United States: 1999–2007. *American Journal of Public Health*, *102*(4), 751–757.

Enax, L., Hu, Y., Trautner, P., & Weber, B. (2015). Nutrition labels influence value computation of food products in the ventromedial prefrontal cortex. *Obesity (Silver Spring, Md.)*, *23*(4), 786–792.

Esliger, D. W., Copeland, J. L., Barnes, J. D., & Tremblay, M. S. (2005). Standardizing and optimizing the use of accelerometer data for free-living physical activity monitoring. *Journal of Physical Activity and Health*, *2*(3), 366–383.

Euston, D. R., Gruber, A. J., & McNaughton, B. L. (2012). The role of medial prefrontal cortex in memory and decision making. *Neuron*, *76*(6), 1057–1070.

Evenson, K. R., Brown, D. R., Pearce, E., Camplain, R., Jernigan, J., Epping, J., Shepard, D. M., & Dorn, J. M. (2016). Evaluation of the Physical Activity and Public Health Course for Practitioners. *Research Quarterly for Exercise & Sport*, *87*(2), 207–213. Retrieved from: http://search.ebscohost.com/login.aspx?direct=true&db=s3h&AN=118224818&site=ehost-live

Evenson, K. R., Goto, M. M., & Furberg, R. D. (2015). Systematic review of the validity and reliability of consumer-wearable activity trackers. *International Journal of Behavioral Nutrition and Physical Activity*, *12*(1), 159.

Eysenbach, G. (2005). The law of attrition. *Journal of Medical Internet Research*, *7*(1), e11.

Fagard, R. H., & Tipton, C. M. (1994). Physical activity, fitness and hypertension. In *Physical activity, fitness, and health: international proceedings and consensus statement. Champaign, IL: Human Kinetics* (pp. 633–655).

Falk, E. B. (2013). Can neuroscience advance our understanding of core questions in Communication Studies? An overview of Communication Neuroscience. *Communication@ the Center*, 77–94.

Falk, E. B., Berkman, E. T., Mann, T., Harrison, B., & Lieberman, M. D. (2010). Predicting persuasion-induced behavior change from the brain. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *30*(25), 8421–8424.

Falk, E. B., Berkman, E. T., Whalen, D., & Lieberman, M. D. (2011). Neural activity during health messaging predicts reductions in smoking above and beyond self-report. *Health Psychology : Official Journal of the Division of Health Psychology, American Psychological Association*, *30*(2), 177–185.

Falk, E. B., O'Donnell, M. B., Cascio, C. N., Tinney, F., Kang, Y., Lieberman, M. D., Taylor, S. E., An, L., Resnicow, K., & Strecher, V. J. (2015). Self-affirmation alters the brain's response to health messages and subsequent behavior change. *Proceedings of the National*

Academy of Sciences of the United States of America, *112*(7), 1977–1982.

Falk, E. B., O'Donnell, M. B., Tompson, S., Gonzalez, R., Dal Cin, S., Strecher, V., Cummings, K. M., & An, L. (2016). Functional brain imaging predicts public health campaign success. *Social Cognitive and Affective Neuroscience*, *11*(2), 204–214.

Falk, E. B., Rameson, L., Berkman, E. T., Liao, B., Kang, Y., Inagaki, T. K., & Lieberman, M. D. (2010). The neural correlates of persuasion: A common network across cultures and media. *Journal of Cognitive Neuroscience*, *22*(11), 2447–2459.

Ferguson, T., Rowlands, A. V, Olds, T., & Maher, C. (2015). The validity of consumer-level, activity monitors in healthy adults worn in free-living conditions: a cross-sectional study. *International Journal of Behavioral Nutrition and Physical Activity*, *12*(1), 42.

Figner, B., Knoch, D., Johnson, E. J., Krosch, A., Lisanby, S. H., Fehr, E., & Weber, E. U. (2010). Lateral prefrontal cortex and self-control in intertemporal choice. *Nature Neuroscience, March*.

Fiordelli, M., Diviani, N., & Schulz, P. J. (2013). Mapping mHealth research: a decade of evolution. *Journal of Medical Internet Research*, *15*(5), e95.

Fiore, M. C., & Baker, T. B. (2009). Stealing a march in the 21st century: accelerating progress in the 100-year war against tobacco addiction in the United States. *American Journal of Public Health*, *99*(7), 1170–1175.

Fishbein, M., & Cappella, J. N. (2006). The role of theory in developing effective health communications. *Journal of Communication*, *56*(s1).

Fishbein, M., Triandis, H. C., Kanfer, F. H., Becker, M., & Middlestadt, S. E. (2000). Factors influencing behavior and behavior change.

Fjeldsoe, B., Neuhaus, M., Winkler, E., & Eakin, E. (2011). Systematic review of maintenance of behavior change following physical activity and dietary interventions. *Health Psychology*, *30*(1), 99.

Floegel, T. A., Giacobbi, Jr., P. R., Dzierzewski, J. M., Aiken-Morgan, A. T., Roberts, B., McCrae, C. S., Marsiske, M., & Buman, M. P. (2015). Intervention Markers of Physical Activity Maintenance in Older Adults. *American Journal of Health Behavior*, *39*(4), 487–499.

Flurry Analytics. (2009). Mobile Apps: Models, Money and Loyalty | Flurry Blog. Retrieved December 17, 2017, from http://flurrymobile.tumblr.com/post/113358847710/mobile-apps-models-money-and-loyalty

Fonda, S. J., Lewis, D. G., & Vigersky, R. A. (2013). Minding the gaps in continuous glucose monitoring: a method to repair gaps to achieve more accurate glucometrics. *Journal of Diabetes Science and Technology*, *7*(1), 88–92.

Forouhi, N. G., Luan, J., Hennings, S., & Wareham, N. J. (2007). Incidence of type 2 diabetes in England and its association with baseline impaired fasting glucose: the Ely study 1990–2000. *Diabetic Medicine*, *24*(2), 200–207.

Forouzanfar, M. H., Liu, P., Roth, G. A., Ng, M., Biryukov, S., Marczak, L., Alexander, L., Estep, K., Hassen Abate, K., Akinyemiju, T. F., Ali, R., Alvis-Guzman, N., Azzopardi, P., Banerjee, A., Bärnighausen, T., Basu, A., Bekele, T., … Murray, C. J. L. (2017). Global Burden of Hypertension and Systolic Blood Pressure of at Least 110 to 115 mm Hg, 1990-2015. *JAMA*, *317*(2), 165.

Freedson, P. S., Melanson, E., & Sirard, J. (1998). Calibration of the Computer Science and

Applications, Inc. accelerometer. *Medicine and Science in Sports and Exercise*, *30*(5), 777–781.

French, D. P., Olander, E. K., Chisholm, A., & Mc Sharry, J. (2014). Which Behaviour Change Techniques Are Most Effective at Increasing Older Adults' Self-Efficacy and Physical Activity Behaviour? A Systematic Review. *Annals of Behavioral Medicine*, *48*(2), 225–234.

Fritschi, C., Park, H., Richardson, A., Park, C., Collins, E. G., Mermelstein, R., Riesche, L., & Quinn, L. (2016). Association Between Daily Time Spent in Sedentary Behavior and Duration of Hyperglycemia in Type 2 Diabetes. *Biological Research For Nursing*, *18*(2), 160–166.

Gardner, B., Smith, L., Lorencatto, F., Hamer, M., & Biddle, S. J. H. (2016). How to reduce sitting time? A review of behaviour change strategies used in sedentary behaviour reduction interventions among adults. *Health Psychology Review*, *10*(1), 89–112.

GBD 2015 Mortality and Causes of Death Collaborators, G. 2015 M. and C. of D. (2016). Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980-2015: a systematic analysis for the Global Burden of Disease Study 2015. *Lancet (London, England)*, *388*(10053), 1459–1544.

Gearhardt, A. N., Yokum, S., Stice, E., Harris, J. L., & Brownell, K. D. (2014). Relation of obesity to neural activation in response to food commercials. *Social Cognitive and Affective Neuroscience*, *9*(7), 932–938.

Genuth, S., Alberti, K. G., Bennett, P., Buse, J., Defronzo, R., Kahn, R., Kitzmiller, J., Knowler, W. C., Lebovitz, H., Lernmark, A., & others. (2003). Expert Committee on the Diagnosis and Classification of Diabetes Mellitus2, the Expert Committee on the Diagnosis and Classification of Diabetes Mellitus. Follow-up report on the diagnosis of diabetes mellitus. *Diabetes Care*, *26*, 3160–3167.

Gero, J., & Kannengiesser, U. (2009). Understanding innovation as change of value systems. *Growth and Development of Computer-Aided Innovation*, 249–257.

Glanz, K., & Bishop, D. B. (2010). The role of behavioral science theory in development and implementation of public health interventions. *Annual Review of Public Health*, *31*, 399–418.

Glasser, M. F., Coalson, T., Robinson, E., Hacker, C., Harwell, J., Yacoub, E., Ugurbil, K., Anderson, J., Beckmann, C. F., & Jenkinson, M. (2015). A Multi-modal parcellation of human cerebral cortex. *Nature*.

Glassman, L. H., Forman, E. M., Herbert, J. D., Bradley, L. E., Foster, E. E., Izzetoglu, M., & Ruocco, A. C. (2016). The Effects of a Brief Acceptance-Based Behavioral Treatment Versus Traditional Cognitive-Behavioral Treatment for Public Speaking Anxiety: An Exploratory Trial Examining Differential Effects on Performance and Neurophysiology. *Behavior Modification*.

Good Things Foundation, & Yates, S. (2017). *The real digital divide?* Retrieved from https://www.goodthingsfoundation.org/sites/default/files/research-publications/ofcom_report_v4_links.pdf

Goodglass, H., & Quadfasel, F. A. (1954). Language laterality in left-handed aphasics. *Brain : A Journal of Neurology*, *77*(4), 521–548.

Gray, L. J., Davies, M. J., Hiles, S., Taub, N. A., Webb, D. R., Srinivasan, B. T., & Khunti, K.

(2012). Detection of impaired glucose regulation and/or type 2 diabetes mellitus, using primary care electronic data, in a multiethnic UK community setting. *Diabetologia*, *55*(4), 959–966.

Gray, L. J., Khunti, K., Edwardson, C., Goldby, S., Henson, J., Morris, D. H., Sheppard, D., Webb, D., Williams, S., Yates, T., & Davies, M. J. (2012). Implementation of the automated Leicester Practice Risk Score in two diabetes prevention trials provides a high yield of people with abnormal glucose tolerance. *Diabetologia*, *55*(12), 3238–3244.

Gray, L. J., Taub, N. A., Khunti, K., Gardiner, E., Hiles, S., Webb, D. R., Srinivasan, B. T., & Davies, M. J. (2010). The Leicester Risk Assessment score for detecting undiagnosed type 2 diabetes and impaired glucose regulation for use in a multiethnic UK setting. *Diabetic Medicine*, *27*(8), 887–895.

Gray, M. (2015). Diabetes: do you mean type 2 or type 1? *The Lancet*, *386*(9996), 856.

Green, L., Myerson, J., Lichtman, D., Rosen, S., & Fry, A. (1996). Temporal discounting in choice between delayed rewards: The role of age and income. *Psychology and Aging*, *11*(1), 79–84.

Greene, J., & Haidt, J. (2002). How (and where) does moral judgment work? *Trends in Cognitive Sciences*, *6*(12), 517–523.

Gregg, E. W., Sattar, N., & Ali, M. K. (2016). The changing face of diabetes complications. *The Lancet. Diabetes & Endocrinology*, *4*(6), 537–47.

Group, D. P. P. R. (2002). Reduction in the incidence of type 2 diabetes with lifestyle intervention or metformin. *N Engl J Med*, *2002*(346), 393–403.

Guariguata, L., Whiting, D. R., Hambleton, I., Beagley, J., Linnenkamp, U., & Shaw, J. E. (2014). Global estimates of diabetes prevalence for 2013 and projections for 2035. *Diabetes Research and Clinical Practice*, *103*(2), 137–149.

Hagströmer, M., Oja, P., & Sjöström, M. (2007). Physical activity and inactivity in an adult population assessed by accelerometry. *Medicine and Science in Sports and Exercise*, *39*(9), 1502–1508.

Hallal, P. C., Andersen, L. B., Bull, F. C., Guthold, R., Haskell, W., Ekelund, U., Group, L. P. A. S. W., & others. (2012). Global physical activity levels: surveillance progress, pitfalls, and prospects. *The Lancet*, *380*(9838), 247–257.

Hamilton, K., Spinks, T., White, K. M., Kavanagh, D. J., & Walsh, A. M. (2016). A psychosocial analysis of parents' decisions for limiting their young child's screen time: An examination of attitudes, social norms and roles, and control perceptions. *British Journal of Health Psychology*, *21*(2), 285–301. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=s3h&AN=114448328&site=ehost-live

Hamilton, M. T., Healy, G. N., Dunstan, D. W., Zderic, T. W., & Owen, N. (2008). Too little exercise and too much sitting: inactivity physiology and the need for new recommendations on sedentary behavior. *Current Cardiovascular Risk Reports*, *2*(4), 292–298.

Hare, T. A., Malmaud, J., & Rangel, A. (2011). Focusing attention on the health aspects of foods changes value signals in vmPFC and improves dietary choice. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *31*(30), 11077–11087.

Hargreaves, T., Nye, M., & Burgess, J. (2010). Making energy visible: A qualitative field study of how householders interact with feedback from smart energy monitors. *Energy Policy*, *38*(10), 6111–6119.

Harris, M. (2001). Frequency of blood glucose monitoring in relation to glycemic control in patients with type 2 diabetes. *Diabetes Care*, *24*(6), 979–982.

Harris, R., Donahue, K., Rathore, S. S., Frame, P., Woolf, S. H., & Lohr, K. N. (2003). Screening adults for type 2 diabetes: a review of the evidence for the U.S. Preventive Services Task Force. *Annals of Internal Medicine*, *138*(3), 215–29. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12558362

Health and Social Care Information Centre. (2013). Quality and Outcomes Framework: Achievement, prevalence and exceptions data, 2012/13. Retrieved from http://content.digital.nhs.uk/catalogue/PUB12262/qual-outc-fram-12-13-rep.pdf

Health Survey for England. (2016). Health Survey for England, 2015: Trend tables. Retrieved from http://content.digital.nhs.uk/article/2021/Website-Search?productid=23717&q=hypertension&sort=Relevance&size=10&page=1&area=both#top

Healy, G. N., Dunstan, D. W., Salmon, J., Cerin, E., Shaw, J. E., Zimmet, P. Z., & Owen, N. (2008). Breaks in sedentary time beneficial associations with metabolic risk. *Diabetes Care*, *31*(4), 661–666.

Healy, G. N., Wijndaele, K., Dunstan, D. W., Shaw, J. E., Salmon, J., Zimmet, P. Z., & Owen, N. (2008). Objectively measured sedentary time, physical activity, and metabolic risk: the Australian Diabetes, Obesity and Lifestyle Study (AusDiab). *Diabetes Care*, *31*(2), 369–371.

Healy, G. N., Winkler, E. A. H., Owen, N., Anuradha, S., & Dunstan, D. W. (2015). Replacing sitting time with standing or stepping: associations with cardio-metabolic risk biomarkers. *European Heart Journal*, *36*(39), 2643–2649.

Henson, J., Yates, T., Biddle, S. J. H., Edwardson, C. L., Khunti, K., Wilmot, E. G., Gray, L. J., Gorely, T., Nimmo, M. A., & Davies, M. J. (2013). Associations of objectively measured sedentary behaviour and physical activity with markers of cardiometabolic health. *Diabetologia*, *56*(5), 1012–1020.

Herdman, M., Gudex, C., Lloyd, A., Janssen, M. F., Kind, P., Parkin, D., Bonsel, G., & Badia, X. (2011). Development and preliminary testing of the new five-level version of EQ-5D (EQ-5D-5L). *Quality of Life Research*, *20*(10), 1727–1736.

Herman, A., Aerts, O., Baeck, M., Bruze, M., De Block, C., Goossens, A., Hamnerius, N., Huygens, S., Maiter, D., Tennstedt, D., Vandeleene, B., & Mowitz, M. (2017). Allergic contact dermatitis caused by isobornyl acrylate in Freestyle® Libre, a newly introduced glucose sensor. *Contact Dermatitis*.

Hermsen, S., Frost, J., Renes, R. J., & Kerkhof, P. (2016). Using feedback through digital technology to disrupt and change habitual behavior: A critical review of current literature. *Computers in Human Behavior*, *57*, 61–74.

Hex, N., Bartlett, C., Wright, D., Taylor, M., & Varley, D. (2012). Estimating the current and future costs of Type 1 and Type 2 diabetes in the UK, including direct health costs and indirect societal and productivity costs. *Diabetic Medicine*, *29*(7), 855–862.

Hoffmann, T. C., Glasziou, P. P., Boutron, I., Milne, R., Perera, R., Moher, D., Altman, D. G.,

Barbour, V., Macdonald, H., Johnston, M., Lamb, S. E., Dixon-Woods, M., McCulloch, P., Wyatt, J. C., Chan, A. W., & Michie, S. (2014). Better reporting of interventions: template for intervention description and replication (TIDieR) checklist and guide. *BMJ (Clinical Research Ed.)*, *348*, g1687.

Hoss, U., Budiman, E. S., Liu, H., & Christiansen, M. P. (2013). Continuous glucose monitoring in the subcutaneous tissue over a 14-day sensor wear period. *Journal of Diabetes Science and Technology*, *7*(5), 1210–1219.

Hu, F. B., Li, T. Y., Colditz, G. A., Willett, W. C., & Manson, J. E. (2003). Television watching and other sedentary behaviors in relation to risk of obesity and type 2 diabetes mellitus in women. *Jama*, *289*(14), 1785–1791.

Inchiostro, S., Candido, R., & Cavalot, F. (2013). How can we monitor glycaemic variability in the clinical setting? *Diabetes, Obesity and Metabolism*, *15*(s2), 13–16.

International Diabetes Federation. (2007). Guidance for Management of Postmeal Glucose. Retrieved from https://www.idf.org/webdata/docs/Guideline_PMG_final.pdf

International Diabetes Federation. (2009). Diabetes Atlas: Fourth edition.

International Diabetes Federation. (2013). Diabetes atlas, sixth edition: Retrieved from http://www.diabetesatlas.org

Jackson, T., Gao, X., & Chen, H. (2014). Differences in neural activation to depictions of physical exercise and sedentary activity: an fMRI study of overweight and lean Chinese women. *International Journal of Obesity (2005)*, *38*(9), 1180–1185.

Jakes, R. W., Day, N. E., Khaw, K. T., Luben, R., Oakes, S., Welch, A., Bingham, S., & Wareham, N. J. (2003). Television viewing and low participation in vigorous recreation are independently associated with obesity and markers of cardiovascular disease risk: EPIC-Norfolk population-based study. *European Journal of Clinical Nutrition*, *57*(9), 1089–1096.

Jarvis, J., Skinner, T. C., Carey, M. E., & Davies, M. J. (2010). How can structured self-management patient education improve outcomes in people with type 2 diabetes? *Diabetes, Obesity and Metabolism*, *12*(1), 12–19.

Jasinska, A. J., Chua, H. F., Ho, S. S., Polk, T. A., Rozek, L. S., & Strecher, V. J. (2012). Amygdala response to smoking-cessation messages mediates the effects of serotonin transporter gene variation on quitting. *NeuroImage*, *60*(1), 766–773.

Johnson, S. C., Baxter, L. C., Wilder, L. S., Pipe, J. G., Heiserman, J. E., & Prigatano, G. P. (2002). Neural correlates of self-reflection. *Brain : A Journal of Neurology*, *125*(Pt 8), 1808–1814.

Kanfer, F. H., & Goldstein, A. P. (1975). *Helping people change: A textbook of methods.* Pergamon Press.

Katzmarzyk, P. T. (2010). Physical activity, sedentary behavior, and health: paradigm paralysis or paradigm shift? *Diabetes*, *59*(11), 2717–2725.

Katzmarzyk, P. T., Church, T. S., Craig, C. L., & Bouchard, C. (2009). Sitting time and mortality from all causes, cardiovascular disease, and cancer. *Medicine and Science in Sports and Exercise*, *41*(5), 998–1005.

Kaye, S. A., White, M. J., & Lewis, I. (2016). The use of neurocognitive methods in assessing health communication messages: A systematic review. *Journal of Health Psychology*.

Kees, J., Burton, S., Andrews, J. C., & Kozup, J. (2006). Tests of graphic visuals and cigarette package warning combinations: implications for the framework convention on tobacco control. *Journal of Public Policy & Marketing*, *25*(2), 212–223.

Kelders, S. M., Kok, R. N., Ossebaard, H. C., & Van Gemert-Pijnen, J. E. (2012). Persuasive System Design Does Matter: a Systematic Review of Adherence to Web-based Interventions. *Journal of Medical Internet Research*, *14*(6), e152.

Kelley, W. M., Macrae, C. N., Wyland, C. L., Caglar, S., Inati, S., & Heatherton, T. F. (2002). Finding the self? An event-related fMRI study. *Journal of Cognitive Neuroscience*, *14*(5), 785–794.

Kelly, M. P. (2016). Digital Technologies and Disease Prevention. *American Journal of Preventive Medicine*, *51*, 861–863.

Kessels, L. T. E., Ruiter, R. A. C., Brug, J., & Jansma, B. M. (2011). The effects of tailored and threatening nutrition information on message attention. Evidence from an event-related potential study. *Appetite*, *56*(1), 32–38.

Kessels, L. T. E., Ruiter, R. A. C., & Jansma, B. M. (2010). Increased attention but more efficient disengagement: Neuroscientific evidence for defensive processing of threatening health information. *Health Psychology*, *29*(4), 346–354.

Kitsiou, S., Paré, G., Jaana, M., & Gerber, B. (2017). Effectiveness of mHealth interventions for patients with diabetes: An overview of systematic reviews. *PloS One*, *12*(3), e0173160.

Klasnja, P., Consolvo, S., & Pratt, W. (2011). How to evaluate technologies for health behavior change in HCI research. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 3063–3072). ACM.

Klasnja, P., & Pratt, W. (2014). Managing health with mobile technology. *Interactions*, *21*(1), 66–69.

Klesges, R. C., Eck, L. H., Mellon, M. W., Fulliton, W., Somes, G. W., & Hanson, C. L. (1990). The accuracy of self-reports of physical activity. *Medicine & Science in Sports & Exercise*.

Klonoff, D. C. (2005). Continuous glucose monitoring: roadmap for 21st century diabetes therapy. *Diabetes Care*, *28*(5), 1231–1239.

Klonoff, D. C. (2007). Benefits and limitations of self-monitoring of blood glucose. *Journal of Diabetes Science and Technology*.

Klonoff, D. C., Bergenstal, R., Blonde, L., Boren, S. A., Church, T. S., Gaffaney, J., Jovanovic, L., Kendall, D. M., Kollman, C., Kovatchev, B. P., Leippert, C., Owens, D. R., Polonsky, W. H., Reach, G., Renard, E., Riddell, M. C., Rubin, R. R., … Wollitzer, A. O. (2008). Consensus report of the coalition for clinical research-self-monitoring of blood glucose. *Journal of Diabetes Science and Technology*, *2*(6), 1030–1053.

Knox, E. C., Esliger, D. W., Biddle, S. J., & Sherar, L. B. (2013). Lack of knowledge of physical activity guidelines: can physical activity promotion campaigns do better? *BMJ Open*, *3*(12), e003633-2013–003633.

Kohl, H. W., Craig, C. L., Lambert, E. V., Inoue, S., Alkandari, J. R., Leetongin, G., Kahlmeier, S., & Group, L. P. A. S. W. (2012). The pandemic of physical inactivity: global action for public health. *The Lancet*, *380*(9838), 294–305.

Kohl, L. F. M., Crutzen, R., & de Vries, N. K. (2013). Online prevention aimed at lifestyle

behaviors: a systematic review of reviews. *Journal of Medical Internet Research*, *15*(7), e146.

Kovatchev, B. P., Patek, S. D., Ortiz, E. A., & Breton, M. D. (2015). Assessing sensor accuracy for non-adjunct use of continuous glucose monitoring. *Diabetes Technology & Therapeutics*, *17*(3), 177–186.

Kreuter, M. W., Strecher, V. J., & Glassman, B. (1999). One size does not fit all: the case for tailoring print materials. *Annals of Behavioral Medicine*, *21*(4), 276–283.

Krogh-Madsen, R., Thyfault, J. P., Broholm, C., Mortensen, O. H., Olsen, R. H., Mounier, R., Plomgaard, P., van Hall, G., Booth, F. W., & Pedersen, B. K. (2010). A 2-wk reduction of ambulatory activity attenuates peripheral insulin sensitivity. *Journal of Applied Physiology (Bethesda, Md.: 1985)*, *108*(5), 1034–1040.

Krugman, D. M., Fox, R. J., Fletcher, J. E., Fischer, P. M., & Rojas, T. H. (1994). Do adolescents attend to warnings in cigarette advertising? An eye-tracking approach. *Journal of Advertising Research*, *34*, 39.

Krum, R. (2013). *Cool infographics: Effective communication with data visualization and design*. John Wiley & Sons.

Kullmann, S., Giel, K. E., Hu, X., Bischoff, S. C., Teufel, M., Thiel, A., Zipfel, S., & Preissl, H. (2014). Impaired inhibitory control in anorexia nervosa elicited by physical activity stimuli. *Social Cognitive and Affective Neuroscience*, *9*(7), 917–923.

Laing, B. Y., Mangione, C. M., Tseng, C.-H., Leng, M., Vaisberg, E., Mahida, M., Bholat, M., Glazier, E., Morisky, D. E., & Bell, D. S. (2014). Effectiveness of a smartphone application for weight loss compared with usual care in overweight primary care patients: a randomized, controlled trial. *Annals of Internal Medicine*, *161*(10 Suppl), S5-12.

Langleben, D. D., Loughead, J. W., Ruparel, K., Hakun, J. G., Busch-Winokur, S., Holloway, M. B., Strasser, A. A., Cappella, J. N., & Lerman, C. (2009). Reduced prefrontal and temporal processing and recall of high "sensation value" ads. *NeuroImage*, *46*(1), 219–225.

Latimer-Cheung, A. E., Rhodes, R. E., Kho, M. E., Tomasone, J. R., Gainforth, H. L., Kowalski, K., Nasuti, G., Perrier, M.-J., & Duggan, M. (2013). Evidence-informed recommendations for constructing and disseminating messages supplementing the new Canadian Physical Activity Guidelines. *BMC Public Health*, *13*(1), 1.

Latimer, A. E., Brawley, L. R., & Bassett, R. L. (2010). A systematic review of three approaches for constructing physical activity messages: What messages work and what improvements are needed? *International Journal of Behavioral Nutrition and Physical Activity*, *7*(1), 36.

Lazar, A., Koehler, C., Tanenbaum, J., & Nguyen, D. H. (2015). Why we use and abandon smart devices. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (pp. 635–646).

Ledger, D., McCaffrey, D., & Partners, E. (2014). Inside Wearables: How the Science of Human Behavior Change O!ers the Secret to Long-Term Engagement. Retrieved from http://endeavaourpartners.net/assets/Endeavour-Partners-Wearables-White-Paper-20141.pdf

LeDoux, J. (2003). Emotion circuits in the brain. Annual review of neuroscience. 2000;23(1):155-84.

Lee, I.-M. (2007). Dose-response relation between physical activity and fitness: even a little is good; more is better. *Jama*, *297*(19), 2137–2139.

Lee, I.-M., Shiroma, E. J., Lobelo, F., Puska, P., Blair, S. N., Katzmarzyk, P. T., & Group, L. P. A. S. W. (2012). Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. *The Lancet*, *380*(9838), 219–229.

Lee, J.-M., Kim, Y., & Welk, G. J. (2014). Validity of consumer-based physical activity monitors. *Med Sci Sports Exerc*, *46*(9), 1840–1848.

Lee, V. K., & Harris, L. T. (2015). How social cognition can inform social decision making. *Neural Basis of Social Learning, Social Deciding, and Other-Regarding Preferences*, 107.

Leniger-Follert, E., & Lübbers, D. W. (1976). Behavior of microflow and localP O 2 of the brain cortex during and after direct electrical stimulation. *Pflügers Archiv*, *366*(1), 39–44.

Levine, B., Turner, G. R., Tisserand, D., Hevenor, S. J., Graham, S., & McIntosh, A. R. (2004). The functional neuroanatomy of episodic and semantic autobiographical remembering: a prospective functional MRI study. *Cognitive Neuroscience, Journal of*, *16*(9), 1633–1646.

Lewis, I. M., Watson, B., White, K. M., & Tay, R. (2007). Promoting public health messages: Should we move beyond fear-evoking appeals in road safety? *Qualitative Health Research*, *17*(1), 61–74.

Lewis, S., Thomas, S. L., Hyde, J., Castle, D., Blood, R. W., & Komesaroff, P. A. (2010). " I don't eat a hamburger and large chips every day!" A qualitative study of the impact of public health messages about obesity on obese adults. *BMC Public Health*, *10*(1), 309.

Lewis, Z. H., Lyons, E. J., Jarvis, J. M., & Baillargeon, J. (2015). Using an electronic activity monitor system as an intervention modality: A systematic review. *BMC Public Health*, *15*(1), 585.

Lieberman, M. D. (2010). Social cognitive neuroscience. *Handbook of Social Psychology*.

Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., Shibuya, K., Adair-Rohani, H., AlMazroa, M. A., Amann, M., Anderson, H. R., & Andrews, K. G. (2013). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010. *The Lancet*, *380*(9859), 2224–2260.

Linden, A., & Fenn, J. (2003). Understanding Gartner's hype cycles. *Strategic Analysis Report N{º} R-20-1971. Gartner, Inc*.

Lintern, G., Waite, T., & Talleur, D. A. (1999). Functional interface design for the modern aircraft cockpit. *The International Journal of Aviation Psychology*, *9*(3), 225–240.

Liu, J. L., Maniadakis, N., Gray, A., & Rayner, M. (2002). The economic burden of coronary heart disease in the UK. *Heart (British Cardiac Society)*, *88*(6), 597–603.

Locke, E. A., Bryan, J. F., & Kendall, L. M. (1968). Goals and intentions as mediators of the effects of monetary incentives on behavior. *Journal of Applied Psychology*, *52*(2), 104.

Lodwig, V., Kulzer, B., Schnell, O., & Heinemann, L. (2014). What Are the Next Steps in Continuous Glucose Monitoring? *Journal of Diabetes Science and Technology*, *8*(2), 397–402.

Logothetis, N. K., Pauls, J., Augath, M., Trinath, T., & Oeltermann, A. (2001). Neurophysiological investigation of the basis of the fMRI signal. *Nature*, *412*(6843), 150–

157.

Loveday, A., Sherar, L. B., Sanders, J. P., Sanderson, P. W., & Esliger, D. W. (2015). Technologies that assess the location of physical activity and sedentary behavior: a systematic review. *Journal of Medical Internet Research*, *17*(8).

Loveday, A., Sherar, L. B., Sanders, J. P., Sanderson, P. W., & Esliger, D. W. (2016). Novel technology to help understand the context of physical activity and sedentary behaviour. *Physiological Measurement*, *37*(10), 1834.

Luijkx, K., Peek, S., & Wouters, E. (2015). "Grandma, You Should Do It—It's Cool" Older Adults and the Role of Family Members in Their Acceptance of Technology. *International Journal of Environmental Research and Public Health*, *12*(12), 15470–15485.

Lyons, E. J., Lewis, Z. H., Mayrsohn, B. G., & Rowland, J. L. (2014). Behavior change techniques implemented in electronic lifestyle activity monitors: a systematic content analysis. *Journal of Medical Internet Research*, *16*(8), e192.

Mackert, M., Champlin, S. E., Holton, A., Muñoz, I. I., & Damásio, M. J. (2014). eHealth and health literacy: A research methodology review. *Journal of Computer-Mediated Communication*, *19*(3), 516–528.

Mainous, A. G., Tanner, R. J., Anton, S. D., Jo, A., & Luetke, M. C. (2017). Physical Activity and Abnormal Blood Glucose Among Healthy Weight Adults. *American Journal of Preventive Medicine*.

Mainous, A. G., Tanner, R. J., Baker, R., Zayas, C. E., & Harle, C. A. (2014). Prevalence of prediabetes in England from 2003 to 2011: population-based, cross-sectional study. *BMJ Open*, *4*(6), e005002.

Maldjian, J. A., Laurienti, P. J., Kraft, R. A., & Burdette, J. H. (2003). An automated method for neuroanatomic and cytoarchitectonic atlas-based interrogation of fMRI data sets. *NeuroImage*, *19*(3), 1233–1239.

Mansoubi, M., Pearson, N., Biddle, S. J., & Clemes, S. A. (2016). Using Sit-to-Stand Workstations in Offices: Is There a Compensation Effect? *Medicine and Science in Sports and Exercise*, *48*(4), 720–725.

Marschollek, M. (2013). A semi-quantitative method to denote generic physical activity phenotypes from long-term accelerometer data–the ATLAS index. *PloS One*, *8*(5), e63522.

Marshall, A. L., Miller, Y. D., Burton, N. W., & Brown, W. J. (2010). Measuring total and domain-specific sitting: a study of reliability and validity. *Medicine and Science in Sports and Exercise*, *42*(6), 1094–1102.

Martin, S., Schneider, B., Heinemann, L., Lodwig, V., Kurth, H.-J., Kolb, H., Scherbaum, W. A., & Group, R. S. (2006). Self-monitoring of blood glucose in type 2 diabetes and long-term outcome: an epidemiological cohort study. *Diabetologia*, *49*(2), 271–278.

Mathers, C. D., & Loncar, D. (2006). Projections of Global Mortality and Burden of Disease from 2002 to 2030. *PLoS Medicine*, *3*(11), e442.

Matthews, C. E., Chen, K. Y., Freedson, P. S., Buchowski, M. S., Beech, B. M., Pate, R. R., & Troiano, R. P. (2008). Amount of time spent in sedentary behaviors in the United States, 2003-2004. *American Journal of Epidemiology*, *167*(7), 875–881.

Matthews, C. E., Keadle, S. K., Moore, S. C., Schoeller, D. S., Carroll, R. J., Troiano, R. P., &

Sampson, J. N. (2017). Measurement of Active and Sedentary Behavior in Context of Large Epidemiologic Studies. *Medicine and Science in Sports and Exercise*.

McAuley, A. (2014). Digital health interventions: widening access or widening inequalities? *Public Health*, *128*(12), 1118–1120.

McCartney, M. (2013). How do we know whether medical apps work? *BMJ (Clinical Research Ed.)*, *346*, f1811.

Medtronic. (2017). Medtronic and Fitbit. Retrieved December 19, 2017, from http://www.medtronic.com/us-en/about/news/news-fitbit-medtronic-partnership.html

Melanson Jr, E. L., & Freedson, P. S. (1995). Validity of the Computer Science and Applications, Inc.(CSA) activity monitor. *Medicine and Science in Sports and Exercise*, *27*(6), 934–940.

Menke, A., Casagrande, S., Geiss, L., & Cowie, C. C. (2015). Prevalence of and Trends in Diabetes Among Adults in the United States, 1988-2012. *JAMA*, *314*(10), 1021.

Mercer, K., Giangregorio, L., Schneider, E., Chilana, P., Li, M., & Grindrod, K. (2016). Acceptance of Commercially Available Wearable Activity Trackers Among Adults Aged Over 50 and With Chronic Illness: A Mixed-Methods Evaluation. *JMIR mHealth and uHealth*, *4*(1), e7.

Michie, S., Abraham, C., Whittington, C., McAteer, J., & Gupta, S. (2009). Effective techniques in healthy eating and physical activity interventions: a meta-regression.

Michie, S., Ashford, S., Sniehotta, F. F., Dombrowski, S. U., Bishop, A., & French, D. P. (2011). A refined taxonomy of behaviour change techniques to help people change their physical activity and healthy eating behaviours: the CALO-RE taxonomy. *Psychology & Health*, *26*(11), 1479–1498.

Michie, S., Richardson, M., Johnston, M., Abraham, C., Francis, J., Hardeman, W., Eccles, M. P., Cane, J., & Wood, C. E. (2013). The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. *Annals of Behavioral Medicine*, *46*(1), 81–95.

Michie, S., van Stralen, M. M., & West, R. (2011). The behaviour change wheel: a new method for characterising and designing behaviour change interventions. *Implementation Science*, *6*(1), 42.

Michie, S., Yardley, L., West, R., Patrick, K., & Greaves, F. (2017). Developing and Evaluating Digital Interventions to Promote Behavior Change in Health and Health Care: Recommendations Resulting From an International Workshop. *Journal of Medical Internet Research*, *19*(6), e232.

Mikus, C. R., Oberlin, D. J., Libla, J. L., Taylor, A. M., Booth, F. W., & Thyfault, J. P. (2012). Lowering physical activity impairs glycemic control in healthy volunteers. *Medicine and Science in Sports and Exercise*, *44*(2), 225–231.

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P., & Stewart, L. A. (2015). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. *Systematic Reviews*, *4*(1), 1.

Morris, J. N., Heady, J. A., Raffle, P. A. B., Roberts, C. G., & Parks, J. W. (1953). Coronary heart-disease and physical activity of work. *The Lancet*, *262*(6796), 1111–1120.

Mozaffarian, D., Benjamin, E. J., Go, A. S., Arnett, D. K., Blaha, M. J., Cushman, M., de Ferranti, S., Després, J.-P., Fullerton, H. J., & Howard, V. J. (2015). Executive summary:

heart disease and stroke statistics—2015 update. *Circulation*, *131*(4), 434–441.

Muir Gray. (2016). *Preventable "lifestyle" diseases: A very modern problem | Oxford Today*. Retrieved from http://www.oxfordtoday.ox.ac.uk/features/preventable-lifestyle-diseases-very-modern-problem

Muñoz, R. F. (2010). Using evidence-based internet interventions to reduce health disparities worldwide. *Journal of Medical Internet Research*, *12*(5), e60.

Murphy, S. L. (2009). Review of physical activity measurement using accelerometers in older adults: considerations for research design and conduct. *Preventive Medicine*, *48*(2), 108–114.

Murray, C. J. L., & Lopez, A. D. (1997a). Alternative projections of mortality and disability by cause 1990–2020: Global Burden of Disease Study. *The Lancet*, *349*(9064), 1498–1504.

Murray, C. J. L., & Lopez, A. D. (1997b). Mortality by cause for eight regions of the world: Global Burden of Disease Study. *The Lancet*, *349*(9061), 1269–1276.

Murray, C. J., Lopez, A. D., & Jamison, D. T. (1994). The global burden of disease in 1990: summary results, sensitivity analysis and future directions. *Bulletin of the World Health Organization*, *72*(3), 495–509. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/8062404

National Institute for Health and Clinical Excellence. (2012). Public health draft guidance. Preventing type 2 diabetes: risk identification and interventions for individuals at high risk. Retrieved from http://guidance.nice.org.uk/PHG/Wave19/62

National Research Council Committee on Population. (2011). *Explaining divergent levels of longevity in high-income countries*. National Academies Press.

Naughton, F., Jamison, J., & Sutton, S. (2013). Attitudes towards SMS text message smoking cessation support: a qualitative study of pregnant smokers. *Health Education Research*, *28*(5), 911–922.

NCD Risk Factor Collaboration (NCD-RisC). (2016). Trends in adult body-mass index in 200 countries from 1975 to 2014: a pooled analysis of 1698 population-based measurement studies with 19·2 million participants. *The Lancet*, *387*(10026), 1377–1396.

Neal, D. T., Wood, W., Labrecque, J. S., & Lally, P. (2012). How do habits guide behavior? Perceived and actual triggers of habits in daily life. *Journal of Experimental Social Psychology*, *48*(2), 492–498.

Newman-Norlund, R. D., Thrasher, J. F., Fridriksson, J., Brixius, W., Froeliger, B., Hammond, D., & Cummings, M. K. (2014). Neural biomarkers for assessing different types of imagery in pictorial health warning labels for cigarette packaging: a cross-sectional study. *BMJ Open*, *4*(12), e006411-2014–006411.

NHS Choices. (2016). NHS stop smoking advisers help you quit - Live Well - NHS Choices. Retrieved January 12, 2018, from https://www.nhs.uk/Livewell/smoking/Pages/NHS-stop-smoking-adviser.aspx

NHS Digital. (2016). *Quality and Outcomes Framework (QOF) 2015/16*. Retrieved from http://content.digital.nhs.uk/qof

NHS Digital. (2017). NHS England: Thousands of people set to access diabetes and obesity prevention services through the touch of a button. Retrieved January 12, 2018, from https://www.england.nhs.uk/2017/11/thousands-of-people-set-to-access-diabetes-and-

obesity-prevention-services-through-the-touch-of-a-button/

NHS England. (2014). No Title. *Five Year Forward View*. Retrieved from https://www.england.nhs.uk/wp-content/uploads/2014/10/5yfv-web.pdf

NHS England. (2016). NHS DPP Expert reference group. Retrieved from www.england.nhs.uk/diabetes/diabetes-prevention/exp-ref-grp/

NICE. (2011). Hypertension in adults: diagnosis and Hypertension in adults: diagnosis and management management Y Your responsibility our responsibility. Retrieved from https://www.nice.org.uk/guidance/cg127/resources/hypertension-in-adults-diagnosis-and-management-pdf-35109454941637

NICE. (2015a). Type 1 diabetes in adults: diagnosis and ype 1 diabetes in adults: diagnosis and management management NICE guideline Y Your responsibility our responsibility. Retrieved from https://www.nice.org.uk/guidance/ng17/resources/type-1-diabetes-in-adults-diagnosis-and-management-pdf-1837276469701

NICE. (2015b). Type 2 diabetes in adults: management ype 2 diabetes in adults: management NICE guideline Y Your responsibility our responsibility. Retrieved from https://www.nice.org.uk/guidance/ng28/resources/type-2-diabetes-in-adults-management-pdf-1837338615493

NICE. (2017). FreeStyle Libre for glucose monitoring: FreeStyle Libre for glucose monitoring. Retrieved from https://www.nice.org.uk/guidance/mib110/resources/freestyle-libre-for-glucose-monitoring-pdf-2285963268047557

Nisbett, R. E., & Wilson, T. D. (1977). The halo effect: Evidence for unconscious alteration of judgments. *Journal of Personality and Social Psychology*, *35*(4), 250.

Noar, S. M., Benac, C. N., & Harris, M. S. (2007). Does tailoring matter? Meta-analytic review of tailored print health behavior change interventions. *Psychological Bulletin*, *133*(4), 673.

Noble, N., Paul, C., Carey, M., Blunden, S., & Turner, N. (2015). A randomised trial assessing the acceptability and effectiveness of providing generic versus tailored feedback about health risks for a high need primary care sample. *BMC Family Practice*, *16*(1), 95.

Norman, C. D., & Skinner, H. A. (2006). eHealth literacy: essential skills for consumer health in a networked world. *J Med Internet Res*, *8*(2), e9.

Norris, S. L., Zhang, X., Avenell, A., Gregg, E., Schmid, C. H., & Lau, J. (2005). Long-term non-pharmacological weight loss interventions for adults with prediabetes. In S. L. Norris (Ed.), *Cochrane Database of Systematic Reviews*. Chichester, UK: John Wiley & Sons, Ltd.

Northoff, G., & Bermpohl, F. (2004). Cortical midline structures and the self. *Trends in Cognitive Sciences*, *8*(3), 102–107.

Northoff, G., Heinzel, A., De Greck, M., Bermpohl, F., Dobrowolny, H., & Panksepp, J. (2006). Self-referential processing in our brain—a meta-analysis of imaging studies on the self. *Neuroimage*, *31*(1), 440–457.

Nyhan, B., Reifler, J., Richey, S., & Freed, G. L. (2014). Effective messages in vaccine promotion: a randomized trial. *Pediatrics*, *133*(4), e835-42.

O'Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American Society for Information Science and Technology*, *59*(6), 938–955.

Ofcom. (2017). The Communications Market Report 2017: UK. Retrieved from https://www.ofcom.org.uk/__data/assets/pdf_file/0017/105074/cmr-2017-uk.pdf

Ogawa, S., Lee, T. M., Kay, A. R., & Tank, D. W. (1990). Brain magnetic resonance imaging with contrast dependent on blood oxygenation. *Proceedings of the National Academy of Sciences of the United States of America*, *87*(24), 9868–9872.

Oliveira, D., Machín, L., Deliza, R., Rosenthal, A., Walter, E. H., Giménez, A., & Ares, G. (2016). Consumers' attention to functional food labels: Insights from eye-tracking and change detection in a case study with probiotic milk. *LWT-Food Science and Technology*, *68*, 160–167.

Olshansky, S. J., Passaro, D. J., Hershow, R. C., Layden, J., Carnes, B. A., Brody, J., Hayflick, L., Butler, R. N., Allison, D. B., & Ludwig, D. S. (2005). A potential decline in life expectancy in the United States in the 21st century. *New England Journal of Medicine*, *352*(11), 1138–1145.

Owen, N., Healy, G. N., Matthews, C. E., & Dunstan, D. W. (2010). Too much sitting: the population health science of sedentary behavior. *Exercise and Sport Sciences Reviews*, *38*(3), 105–113.

Paffenbarger Jr, R. S., Laughlin, M. E., Gima, A. S., & Black, R. A. (1970). Work activity of longshoremen as related to death from coronary heart disease and stroke. *New England Journal of Medicine*, *282*(20), 1109–1114.

Pagliari, C. (2007). Design and evaluation in eHealth: challenges and implications for an interdisciplinary field. *Journal of Medical Internet Research*, *9*(2).

Pandey, A., Hasan, S., Dubey, D., & Sarangi, S. (2013). Smartphone apps as a source of cancer information: changing trends in health information-seeking behavior. *Journal of Cancer Education*, *28*(1), 138–142.

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, *18*(1), 59–74.

Patel, M. S., Asch, D. A., & Volpp, K. G. (2015). Wearable devices as facilitators, not drivers, of health behavior change. *Jama*, *313*(5), 459–460.

Patrick, K., Hekler, E., D, E., & et al. (2016). Rapid rate of technological development and its implications for research on digital behavior interventions. *Am J Prev Med, In press*.

Peddie, M. C., Bone, J. L., Rehrer, N. J., Skeaff, C. M., Gray, A. R., & Perry, T. L. (2013). Breaking prolonged sitting reduces postprandial glycemia in healthy, normal-weight adults: a randomized crossover trial. *The American Journal of Clinical Nutrition*, *98*(2), 358–366.

Perrin, A. J., Caren, N., Skinner, A. C., Odulana, A., & Perrin, E. M. (2016). The unbuilt environment: culture moderates the built environment for physical activity. *BMC Public Health*, *16*(1), 1227.

Petry, N. M. (2001). Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls. *Psychopharmacology*, *154*(3), 243–50. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11351931

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In *Communication and persuasion* (pp. 1–24). Springer.

Phan, K. L., Taylor, S. F., Welsh, R. C., Ho, S.-H., Britton, J. C., & Liberzon, I. (2004). Neural correlates of individual ratings of emotional salience: a trial-related fMRI study.

Neuroimage, *21*(2), 768–780.

Pickup, J. C., Ford Holloway, M., & Samsi, K. (2015). Real-time continuous glucose monitoring in type 1 diabetes: a qualitative framework analysis of patient narratives. *Diabetes Care*, *38*(4), 544–550.

Piwek, L., Ellis, D. A., Andrews, S., & Joinson, A. (2016). The rise of consumer health wearables: promises and barriers. *PLoS Med*, *13*(2), e1001953.

Plasqui, G., & Westerterp, K. R. (2007). Physical activity assessment with accelerometers: an evaluation against doubly labeled water. *Obesity*, *15*(10), 2371–2379.

Poldrack, R. A. (2006). Can cognitive processes be inferred from neuroimaging data? *Trends in Cognitive Sciences*, *10*(2), 59–63.

Polivy, J., & Herman, C. P. (2002). If at first you don't succeed: False hopes of self-change. *American Psychologist*, *57*(9), 677.

Polonsky, W. H., & Fisher, L. (2013). Self-monitoring of blood glucose in noninsulin-using type 2 diabetic patients: right answer, but wrong question: self-monitoring of blood glucose can be clinically valuable for noninsulin users. *Diabetes Care*, *36*(1), 179–182.

Polonsky, W. H., Fisher, L., Hessler, D., & Edelman, S. V. (2014). What is so tough about self-monitoring of blood glucose? Perceived obstacles among patients with Type 2 diabetes. *Diabetic Medicine*, *31*(1), 40–46.

Powell, A. C., Landman, A. B., & Bates, D. W. (2014). In Search of a Few Good Apps. *JAMA*, *311*(18), 1851.

Powers, M. A., Bardsley, J., Cypress, M., Duker, P., Funnell, M. M., Fischl, A. H., Maryniuk, M. D., Siminerio, L., & Vivian, E. (2015). Diabetes self-management education and support in type 2 diabetes: a joint position statement of the American Diabetes Association, the American Association of Diabetes Educators, and the Academy of Nutrition and Dietetics. *The Diabetes Educator*, *41*(4), 417–430.

Pramis, J. (2013). Study shows that 90 percent of apps are downloaded once then deleted | Digital Trends. Retrieved November 6, 2017, from https://www.digitaltrends.com/mobile/16-percent-of-mobile-userstry-out-a-buggy-app-more-than-twice/

Preece, S. J., Goulermas, J. Y., Kenney, L. P. J., Howard, D., Meijer, K., & Crompton, R. (2009). Activity identification using body-mounted sensors—a review of classification techniques. *Physiological Measurement*, *30*(4), R1.

Prince, S. A., Adamo, K. B., Hamel, M. E., Hardt, J., Gorber, S. C., & Tremblay, M. (2008). A comparison of direct versus self-report measures for assessing physical activity in adults: a systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *5*(1), 56.

Research2Guidance. (2016). Diabetes App Market Report 2016-2021. Retrieved from https://research2guidance.com/product/diabetes-app-market-report-2016-2021/

Research2Guidance. (2017). *mHealth App Economics 2017: Current Status and Future Trends in Mobile Health*. Retrieved from https://research2guidance.com/wp-content/uploads/2017/11/R2G-mHealth-Developer-Economics-2017-Status-And-Trends.pdf

Reubi, D. (2016). Modernisation, smoking and chronic disease: Of temporality and spatiality in global health. *Health & Place*, *39*, 188–195.

Reynolds, A. N., Mann, J. I., Williams, S., & Venn, B. J. (2016). Advice to walk after meals is more effective for lowering postprandial glycaemia in type 2 diabetes mellitus than advice that does not specify timing: a randomised crossover study. *Diabetologia*, *59*(12), 2572–2578.

Riley, W. T., Serrano, K. J., Nilsen, W., & Atienza, A. A. (2015). Mobile and wireless technologies in health behavior and the potential for intensively adaptive interventions. *Current Opinion in Psychology*, *5*, 67–71.

Rodbard, D. (2011). Glycemic variability: measurement and utility in clinical medicine and research—one viewpoint. *Diabetes Technology & Therapeutics*, *13*(11), 1077.

Rollo, M. E., Aguiar, E. J., Williams, R. L., Wynne, K., Kriss, M., Callister, R., & Collins, C. E. (2016). eHealth technologies to support nutrition and physical activity behaviors in diabetes self-management. *Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy*, *9*, 381.

Rosenberger, M. E., Buman, M. P., Haskell, W. L., McConnell, M. V, & Carstensen, L. L. (2016). Twenty-four Hours of Sleep, Sedentary Behavior, and Physical Activity with Nine Wearable Devices. *Medicine and Science in Sports and Exercise*, *48*(3), 457–465.

Rothman, A. J., & Salovey, P. (1997). Shaping perceptions to motivate healthy behavior: the role of message framing. *Psychological Bulletin*, *121*(1), 3.

Rowsell, A., Muller, I., Murray, E., Little, P., Byrne, C. D., Ganahl, K., Muller, G., Gibney, S., Lyles, C. R., Lucas, A., Nutbeam, D., & Yardley, L. (2015). Views of People With High and Low Levels of Health Literacy About a Digital Intervention to Promote Physical Activity for Diabetes: A Qualitative Study in Five Countries. *Journal of Medical Internet Research*, *17*(10), e230.

Sacks, D. B., Arnold, M., Bakris, G. L., Bruns, D. E., Horvath, A. R., Kirkman, M. S., Lernmark, A., Metzger, B. E., Nathan, D. M., & Biochemistry, N. A. of C. (2011). Position statement executive summary: guidelines and recommendations for laboratory analysis in the diagnosis and management of diabetes mellitus. *Diabetes Care*, *34*(6), 1419–1423.

Sallis, J. F., & Saelens, B. E. (2000). Assessment of physical activity by self-report: status, limitations, and future directions. *Research Quarterly for Exercise and Sport*, *71*(sup2), 1–14.

Salmon, J., Bauman, A., Crawford, D., Timperio, A., & Owen, N. (2000). The association between television viewing and overweight among Australian adults participating in varying levels of leisure-time physical activity. *International Journal of Obesity*, *24*(5), 600.

Sanders, J. P., Loveday, A., Pearson, N., Edwardson, C., Yates, T., Biddle, S. J., & Esliger, D. W. (2016). Devices for Self-Monitoring Sedentary Time or Physical Activity: A Scoping Review. *Journal of Medical Internet Research*, *18*(5), e90.

Santaguida, P. L., Balion, C., Hunt, D., Morrison, K., Gerstein, H., Raina, P., Booker, L., & Yazdi, H. (2005). Diagnosis, prognosis, and treatment of impaired glucose tolerance and impaired fasting glucose. *Evid Rep Technol Assess (Summ)*, *128*(1).

Schillinger, D., Piette, J., Grumbach, K., Wang, F., Wilson, C., Daher, C., Leong-Grotz, K., Castro, C., & Bindman, A. B. (2003). Closing the loop: physician communication with diabetic patients who have low health literacy. *Archives of Internal Medicine*, *163*(1), 83–90.

Schneider, F., Bolier, L., de Vries, H., & van Osch, L. (2016). Using a qualitative approach to assess motives for non-uptake and disengagement in digital interventions. *European Health Psychologist*, *18*(S), 312.

Scott, H., Fawkner, S., Oliver, C., & Murray, A. (2016). Why healthcare professionals should know a little about infographics. *British Journal of Sports Medicine*, *50*(18), 1104–1105.

Seelig, D., Wang, A.-L., Jaganathan, K., Loughead, J. W., Blady, S. J., Childress, A. R., Romer, D., & Langleben, D. D. (2014). Low message sensation health promotion videos are better remembered and activate areas of the brain associated with memory encoding. *PloS One*, *9*(11), e113256.

Serrano, K. J., Coa, K. I., Yu, M., Wolff-Hughes, D. L., & Atienza, A. A. (2017). Characterizing user engagement with health app data: a data mining approach. *Translational Behavioral Medicine*, *7*(2), 277–285.

Shephard, R. J. (1995). Physical activity, fitness, and health: the current consensus. *Quest*, *47*(3), 288–303.

Shih, P. C., Han, K., Poole, E. S., Rosson, M. B., & Carroll, J. M. (2015). Use and adoption challenges of wearable activity trackers. *iConference 2015 Proceedings*.

Skinner, C. S., Strecher, V. J., & Hospers, H. (1994). Physicians' recommendations for mammography: do tailored messages make a difference? *American Journal of Public Health*, *84*(1), 43–49.

Soliman, A., DeSanctis, V., Yassin, M., Elalaily, R., & Eldarsy, N. E. (2014). Continuous glucose monitoring system and new era of early diagnosis of diabetes in high risk groups. *Indian Journal of Endocrinology and Metabolism*, *18*(3), 274–282.

Sport England. (2017). Active Lives Survey 2015-16. Retrieved from https://www.sportengland.org/media/11498/active-lives-survey-yr-1-report.pdf

Spruijt-Metz, D., Wen, C. K. F., O'Reilly, G., Li, M., Lee, S., Emken, B. A., Mitra, U., Annavaram, M., Ragusa, G., & Narayanan, S. (2015). Innovations in the Use of Interactive Technology to Support Weight Management. *Current Obesity Reports*, *4*(4), 510–519.

Stamatakis, E., Coombs, N., Jago, R., Gama, A., Mourão, I., Nogueira, H., Rosado, V., & Padez, C. (2013). Type-specific screen time associations with cardiovascular risk markers in children. *American Journal of Preventive Medicine*, *44*(5), 481–488.

Stamatakis, E., Pulsford, R. M., Brunner, E. J., Britton, A. R., Bauman, A. E., Biddle, S. J. H., & Hillsdon, M. (2017). Sitting behaviour is not associated with incident diabetes over 13 years: the Whitehall II cohort study. *Br J Sports Med*, bjsports-2016-096723.

Statistica. (2017). Android: market share in the UK 2011-2017 | Statistics. Retrieved December 17, 2017, from https://www.statista.com/statistics/271240/android-market-share-in-the-united-kingdom-uk/

Statistica. (2018). Number of smartphone users worldwide from 2014 to 2020. Retrieved from https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/

Statistics, O. for N. (2016). 2014 Opinions and Lifestyle Survey. Retrieved from http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/rel/ghs/general-lifestyle-survey/2011/index.html

Steinhubl, S. R., Muse, E. D., & Topol, E. J. (2013). Can mobile health technologies transform health care? *Jama*, *310*(22), 2395–2396.

Stephenson, A., McDonough, S. M., Murphy, M. H., Nugent, C. D., & Mair, J. L. (2017). Using computer, mobile and wearable technology enhanced interventions to reduce sedentary behaviour: a systematic review and meta-analysis. *International Journal of Behavioral Nutrition and Physical Activity*, *14*(1), 105.

Stone, D., Jarrett, C., Woodroffe, M., & Minocha, S. (2005). *User interface design and evaluation*. Morgan Kaufmann.

Strasser, A. A., Tang, K. Z., Romer, D., Jepson, C., & Cappella, J. N. (2012). Graphic Warning Labels in Cigarette Advertisements: Recall and Viewing Patterns. *American Journal of Preventive Medicine*, *43*(1), 41–47.

Strecher, V. J., Kreuter, M., Den Boer, D.-J., Kobrin, S., Hospers, H. J., & Skinner, C. S. (1994). The effects of computer-tailored smoking cessation messages in family practice settings. *Journal of Family Practice*, *39*(3), 262–270.

Strecher, V. J., McClure, J. B., Alexander, G. L., Chakraborty, B., Nair, V. N., Konkel, J. M., Greene, S. M., Collins, L. M., Carlier, C. C., & Wiese, C. J. (2008). Web-based smoking-cessation programs: results of a randomized trial. *American Journal of Preventive Medicine*, *34*(5), 373–381.

Swan, M. (2009). Emerging patient-driven health care models: an examination of health social networks, consumer personalized medicine and quantified self-tracking. *International Journal of Environmental Research and Public Health*, *6*(2), 492–525.

Tabák, A. G., Herder, C., Rathmann, W., Brunner, E. J., & Kivimäki, M. (2012). Prediabetes: a high-risk state for diabetes development. *The Lancet*, *379*(9833), 2279–2290.

Taylor, S. E. (1971). *The dynamic activity of reading: A model of the process*. Educational Developmental Laboratories.

Teare, H. J. A., Morrison, M., Whitley, E. A., & Kaye, J. (2015). Towards "Engagement 2.0": Insights from a study of dynamic consent with biobank participants. *Digital Health*, *1*, 2055207615605644.

Thompson, D., & Batterham, A. M. (2013). Towards integrated physical activity profiling. *PloS One*, *8*(2), e56427.

Thompson, D., Peacock, O., Western, M., & Batterham, A. M. (2015). Multidimensional physical activity: an opportunity, not a problem. *Exercise and Sport Sciences Reviews*, *43*(2), 67–74.

Thorp, A. A., Healy, G. N., Owen, N., Salmon, J., Ball, K., Shaw, J. E., Zimmet, P. Z., & Dunstan, D. W. (2010). Deleterious associations of sitting time and television viewing time with cardiometabolic risk biomarkers: Australian Diabetes, Obesity and Lifestyle (AusDiab) study 2004-2005. *Diabetes Care*, *33*(2), 327–334.

Todorov, A., Baron, S. G., & Oosterhof, N. N. (2008). Evaluating face trustworthiness: a model based approach. *Social Cognitive and Affective Neuroscience*, *3*(2), 119–127.

Tognoli, E., & Kelso, J. A. S. (2015). The coordination dynamics of social neuromarkers. *Frontiers in Human Neuroscience*, *9*.

Tremblay, M. S., Aubert, S., Barnes, J. D., Saunders, T. J., Carson, V., Latimer-Cheung, A. E., Chastin, S. F. M., Altenburg, T. M., & Chinapaw, M. J. M. (2017). Sedentary Behavior Research Network (SBRN)--Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity*, *14*(1), 75.

Tremblay, M. S., Colley, R. C., Saunders, T. J., Healy, G. N., & Owen, N. (2010). Physiological

and health implications of a sedentary lifestyle. *Applied Physiology, Nutrition, and Metabolism*, *35*(6), 725–740.

Troiano, R. P., Berrigan, D., Dodd, K. W., Masse, L. C., Tilert, T., & McDowell, M. (2008). Physical activity in the United States measured by accelerometer. *Medicine and Science in Sports and Exercise*, *40*(1), 181.

Troiano, R. P., McClain, J. J., Brychta, R. J., & Chen, K. Y. (2014). Evolution of accelerometer methods for physical activity research. *British Journal of Sports Medicine*, *48*(13), 1019–1023.

Tudor-Locke, C., & Lutes, L. (2009). Why do pedometers work? *Sports Medicine*, *39*(12), 981–993.

Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., Mazoyer, B., & Joliot, M. (2002). Automated anatomical labeling of activations in SPM using a macroscopic anatomical parcellation of the MNI MRI single-subject brain. *NeuroImage*, *15*(1), 273–289.

UK Department of Health. (2009). Change4Life Marketing Strategy.

UK Department of Health. (2011a). Physical Activity Guidelines for Adults. Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/213740/dh_128145.pdf

UK Department of Health. (2011b). Physical Activity Guidelines for Adults (19-64 years). Retrieved from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/213740/dh_128145.pdf

US Food and Drug Adminstration. (2016). FDA Executive Summary: Prepared for the July 21, 2016 meeting of the Clinical Chemistry and Clinical Toxicology Devices Panel P120005/S041 Dexcom G5 Mobile Continuous Glucose Monitoring System Dexcom, Inc. Retrieved from: https://www.fda.gov/downloads/AdvisoryCommittees/MedicalDevices/ClinicalChemistryToxicologyDevicesPanel/UCM511810.pdf

Van Dam, S. S., Bakker, C. A., & Van Hal, J. D. M. (2010). Home energy monitors: impact over the medium-term. *Building Research & Information*, *38*(5), 458–469.

Van Dam, S. S., Bakker, C. A., & Van Hal, J. D. M. (2012). Insights into the design, use and implementation of home energy management systems. *Journal of Design Research*, *14*, 86.

van der Weegen, S., Verwey, R., Spreeuwenberg, M., Tange, H., van der Weijden, T., & de Witte, L. (2013). The development of a mobile monitoring and feedback tool to stimulate physical activity of people with a chronic disease in primary care: a user-centered design. *JMIR mHealth and uHealth*, *1*(2), e8.

Vecchiato, G., Astolfi, L., De Vico Fallani, F., Toppi, J., Aloise, F., Bez, F., Wei, D., Kong, W., Dai, J., & Cincotti, F. (2011). On the use of EEG or MEG brain imaging tools in neuromarketing research. *Computational Intelligence and Neuroscience*, *2011*, 3.

Velazquez, C. E., & Pasch, K. E. (2014). Attention to Food and Beverage Advertisements as Measured by Eye-Tracking Technology and the Food Preferences and Choices of Youth. *Journal of the Academy of Nutrition and Dietetics*, *114*(4), 578–582.

Versace, F., Engelmann, J. M., Jackson, E. F., Costa, V. D., Robinson, J. D., Lam, C. Y.,

Minnix, J. A., Brown, V. L., Wetter, D. W., & Cinciripini, P. M. (2011). Do brain responses to emotional images and cigarette cues differ? An fMRI study in smokers. *European Journal of Neuroscience*, *34*(12), 2054–2063.

Vigersky, R. A., Fonda, S. J., Chellappa, M., Walker, M. S., & Ehrhardt, N. M. (2012). Short- and long-term effects of real-time continuous glucose monitoring in patients with type 2 diabetes. *Diabetes Care*, *35*(1), 32–38.

Vollstadt-Klein, S., Kobiella, A., Buhler, M., Graf, C., Fehr, C., Mann, K., & Smolka, M. N. (2011). Severity of dependence modulates smokers' neuronal cue reactivity and cigarette craving elicited by tobacco advertisement. *Addiction Biology*, *16*(1), 166–175.

Wagner, J., Tennen, H., & Wolpert, H. (2012). Continuous glucose monitoring: a review for behavioral researchers. *Psychosomatic Medicine*, *74*(4), 356–365.

Wakefield, M. A., Durkin, S., Spittal, M. J., Siahpush, M., Scollo, M., Simpson, J. A., Chapman, S., White, V., & Hill, D. (2008). Impact of tobacco control policies and mass media campaigns on monthly adult smoking prevalence. *American Journal of Public Health*, *98*(8), 1443–1450.

Wakefield, M. A., Loken, B., & Hornik, R. C. (2010). Use of mass media campaigns to change health behaviour. *The Lancet*, *376*(9748), 1261–1271.

Walker, E. A., Mertz, C. K., Kalten, M. R., & Flynn, J. (2003). Risk perception for developing diabetes: comparative risk judgments of physicians. *Diabetes Care*, *26*(9), 2543–2548.

Wang, A. L., Lowen, S. B., Romer, D., Giorno, M., & Langleben, D. D. (2015). Emotional reaction facilitates the brain and behavioural impact of graphic cigarette warning labels in smokers. *Tobacco Control*, *24*(3), 225–232.

Wang, A. L., Ruparel, K., Loughead, J. W., Strasser, A. A., Blady, S. J., Lynch, K. G., Romer, D., Cappella, J. N., Lerman, C., & Langleben, D. D. (2013). Content matters: neuroimaging investigation of brain and behavioral impact of televised anti-tobacco public service announcements. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *33*(17), 7420–7427.

Wang, Y., & Hamilton, A. F. de C. (2014). Anterior medial prefrontal cortex implements social priming of mimicry. *Social Cognitive and Affective Neuroscience*, *10*(4), 486–493.

Warburton, D. E., Nicol, C. W., & Bredin, S. S. (2006). Health benefits of physical activity: the evidence. *CMAJ : Canadian Medical Association Journal = Journal de l'Association Medicale Canadienne*, *174*(6), 801–809.

Warburton, D. E. R., Jamnik, V. K., Bredin, S. S. D., Gledhill, N., & Collaboration, P.-Q. R. (2011). The physical activity readiness questionnaire (PAR-Q) and electronic physical activity readiness medical examination (ePARmed-X). *Health Fitness J Can*, *4*(2), 3–23.

Webb, D. R., Gray, L. J., Khunti, K., Srinivasan, B., Taub, N., Campbell, S., Barnett, J., Farooqi, A., Echouffo-Tcheugui, J. B., Griffin, S. J., Wareham, N. J., & Davies, M. J. (2011). Screening for diabetes using an oral glucose tolerance test within a western multi-ethnic population identifies modifiable cardiovascular risk: the ADDITION-Leicester study. *Diabetologia*, *54*(9), 2237–2246.

Webb, O. J., & Eves, F. F. (2005). Promoting stair use: single versus multiple stair-riser messages. *American Journal of Public Health*, *95*(9), 1543–1544.

Weber, R., Mangus, J. M., & Huskey, R. (2015). Brain imaging in communication research: A practical guide to understanding and evaluating fMRI studies. *Communication Methods*

and Measures, *9*(1–2), 5–29.

Weller, I. M. R., Thomas, S. G., Corey, P. N., & Cox, M. H. (1993). Prediction of Maximal Oxygen Uptake From a Modified Canadian Aerobic Fitness Test. *Canadian Journal of Applied Physiology*, *18*(2), 175–188.

Wen, C. P., & Wu, X. (2012). Stressing harms of physical inactivity to promote exercise. *The Lancet*, *380*(9838), 192.

Western, M. J., Peacock, O. J., Stathi, A., & Thompson, D. (2015). The understanding and interpretation of innovative technology-enabled multidimensional physical activity feedback in patients at risk of future chronic disease. *PloS One*, *10*(5), e0126156.

Wheeler, S. C., DeMarree, K. G., & Petty, R. E. (2007). Understanding the role of the self in prime-to-behavior effects: The active-self account. *Personality and Social Psychology Review*, *11*(3), 234–261.

Whelan, M. E., Morgan, P. S., Sherar, L. B., Orme, M. W., & Esliger, D. W. (2017). Can functional magnetic resonance imaging studies help with the optimization of health messaging for lifestyle behavior change? A systematic review. *Preventive Medicine*, *99*(June), 185–196.

Whelan, M., Kingsnorth, A., Orme, M., Sherar, L., & Esliger, D. (2017). Sensing interstitial glucose to nudge active lifestyles (SIGNAL): feasibility of combining novel self-monitoring technologies for persuasive behaviour change. *BMJ Open*, *7*(10).

Whelan, M., Morgan, P., Sherar, L., Kingsnorth, A., Magistro, D., & Esliger, D. (2017). Brain Activation in Response to Personalized Behavioral and Physiological Feedback From Self-Monitoring Technology: Pilot Study. *Journal of Medical Internet Research*, *19*(11), e384.

White, D. K., Gabriel, K. P., Kim, Y., Lewis, C. E., & Sternfeld, B. (2015). Do Short Spurts of Physical Activity Benefit Cardiovascular Health? The CARDIA Study. *Medicine and Science in Sports and Exercise*, *47*(11), 2353–2358.

Wijndaele, K., Brage, S., Besson, H., Khaw, K. T., Sharp, S. J., Luben, R., Wareham, N. J., & Ekelund, U. (2011). Television viewing time independently predicts all-cause and cardiovascular mortality: the EPIC Norfolk study. *International Journal of Epidemiology*, *40*(1), 150–159.

Wijndaele, K., Orrow, G., Ekelund, U., Sharp, S. J., Brage, S., Griffin, S. J., & Simmons, R. K. (2014). Increasing objectively measured sedentary time increases clustered cardiometabolic risk: a 6 year analysis of the ProActive study. *Diabetologia*, *57*(2), 305–312.

Wood, G., & Newborough, M. (2003). Dynamic energy-consumption indicators for domestic appliances: environment, behaviour and design. *Energy and Buildings*, *35*(8), 821–841.

Wood, W., & Neal, D. T. (2007). A new look at habits and the habit-goal interface. *Psychological Review*, *114*(4), 843.

World Health Organisation. (2016). Global Report on Diabetes. *ISBN*, *978*, 92–4. Retrieved from http://www.who.int/about/licensing/

World Health Organization. (2002). *The world health report 2002: reducing risks, promoting healthy life*. World Health Organization.

World Health Organization. (2005). Preventing chronic diseases: a vital investment: WHO global report.

World Health Organization. (2009). Framework Convention on Tobacco Control. Retrieved from http://www.who.int/fctc/FCTC-2009-1-en.pdf

World Health Organization. (2011a). Causes of death 2008: Data sources and methods. Retrieved from http://www.who.int/healthinfo/global_burden_disease/cod_2008_sources_methods.pdf

World Health Organization. (2011b). Waist circumference and waist-hip ratio: Report of a WHO expert consultation, Geneva, 8-11 December 2008.

World Health Organization. (2013a). Cardiovascular diseases (CVDs). Fact sheet no. 317 [Online]. Retrieved from http://www.who.int/mediacentre/factsheets/fs317/en/

World Health Organization. (2013b). Global action plan for the prevention and control of noncommunicable diseases 2013-2020.

World Health Organization. (2014). *Global status report on noncommunicable diseases 2014.* World Health Organization.

World Health Organization. (2015). Noncommunicable Diseases: Fact Sheet. Retrieved from http://www.who.int/mediacentre/factsheets/fs355/en/

Wright, S. P., Hall Brown, T. S., Collier, S. R., & Sandberg, K. (2017). How consumer physical activity monitors could transform human physiology research. *American Journal of Physiology - Regulatory, Integrative and Comparative Physiology*, *312*(3), R358–R367.

Yardley, L., Spring, B. J., Riper, H., Morrison, L. G., Crane, D. H., Curtis, K., Merchant, G. C., Naughton, F., & Blandford, A. (2016). Understanding and promoting effective engagement with digital behavior change interventions. *American Journal of Preventive Medicine*, *51*(5), 833–842.

Zhang, Berthelot, & Lo. (2016). Wireless wearable photoplethysmography sensors for continuous blood pressure monitoring. In *2016 IEEE Wireless Health (WH)* (pp. 1–8).

Appendices

Appendix A

Study One: Copy of Publication.

Preventive Medicine 99 (2017) 185–196

Contents lists available at ScienceDirect

Preventive Medicine

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Review Article

Can functional magnetic resonance imaging studies help with the optimization of health messaging for lifestyle behavior change? A systematic review

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ABSTRACT

Unhealthy behaviors, including smoking, poor nutrition, excessive alcohol consumption, physical inactivity and sedentary lifestyles, are global risk factors for non-communicable diseases and premature death. Functional magnetic resonance imaging (fMRI) offers a unique approach to optimize health messages by examining how the brain responds to information relating to health. Our aim was to systematically review fMRI studies that have investigated variations in brain activation in response to health messages relating to (i) smoking; (ii) alcohol consumption; (iii) physical activity; (iv) diet; and (v) sedentary behavior. The electronic databases used were Medline/PubMed, Web of Science (Core Collection), PsychINFO, SPORTDiscuss, Cochrane Library and Open Grey. Studies were included if they investigated subjects aged ≥ 10 years and were published before January 2017. Of the 13,836 studies identified in the database search, 18 studies (smoking k = 15; diet k = 2; physical activity/sedentary behavior k = 1) were included in the review. The prefrontal cortex was activated in seven (47%) of the smoking-related studies and the physical activity study. Results suggest that activation of the ventromedial, dorsolateral and medial prefrontal cortex regions were predictive of subsequent behavior change following exposure to aversive anti-smoking stimuli. Studies investigating the neurological responses to anti-smoking material were most abundant. Of note, the prefrontal cortex and amygdala were most commonly activated in response to health messages across lifestyle behaviors. The review highlights an important disparity between research focusing on different lifestyle behaviors. Insights from smoking literature suggest fMRI may help to optimize health messaging in relation to other lifestyle behaviors.

Contents

Abbreviations: PSA, public service announcement; MRI, magnetic resonance imaging; fMRI, functional magnetic resonance imaging; NCD, non-communicable diseases; UK, United Kingdom; USA, United States of America; BOLD, blood oxygen level dependent; PRISMA, preferred reporting items for systematic reviews and meta-analyses; FDA, food and drug administration.

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Appendix B

Study One: Functional MRI Acquisition Overview.

Study	Task design	Magnet (T)	TE (ms)	TR (ms)	Flip angle (degrees)	Field of View (mm)	Slice Thickness (mm)
(Chua et al., 2009)	Detail not provided	Detail not provided	Detail not provided	Detail not provided	Detail not provided	Detail not provided	Detail not provided
(Chua et al., 2009)	Mixed. Blocked: blocks 65 secs; fixation 20 secs. Event-related: trials 3.5 secs; fixation 4, 6 or 8 secs (jittered). Total task 32 mins.	3T GE Signa scanner	30	2000	80	220	3.4
(Chua et al., 2011)	Blocked. Initial fixation 10 secs; blocks 24 secs (5 trials); fixation 7 secs (4-10 secs).	3T GE Signa Excite 2 scanner	30	2000	90	220	3
(Cooper et al., 2015)	Blocked. Trials 17.7 secs (13.9-30 secs); rate ads 4 secs; fixation ITI 4.1 secs (3.1-7.5 secs).	3T GE Signa scanner	30	2000	90	220	3
(Dinh-Williams et al., 2014)	Blocked. Aversive blocks and appetitive blocks; fixation 15 secs; trials 4 secs; blank screen ISI 0.5 to 1.5 secs.	3T Siemens TRIO scanner	30	3000	90	Detail not provided	3.5

(Dinh-Williams et al., 2014)	Blocked. Blocks 25 secs (5 trials); trials 4 secs; blank screen ISI 1 second (0.5 to 1.5 secs).	3T Siemens TRIO scanner	30	3000	90	Detail not provided	3.5
(Do & Galvan, 2015)	Event-related. Trials 6 secs; button response 2 secs; ISI 10 secs (jittered).	3T Siemens TRIO scanner	30	2000	90	Detail not provided	4
(Enax et al., 2015)	Event-related. Trials 5 secs; fixation 4-6 secs; button response ITI 4-6 secs. Total task 30-40 mins.	1.5T Siemens Avanto scanner	45	2500	90	192	3
(Falk et al., 2011)	Blocked. 14 ads 30 secs; 2 ads 15 secs; button response 4 secs; fixation; additional fixations every 4 blocks.	3T Siemens Trio scanner	30	2000	90	192	4
(Falk et al., 2016)	Trial 4 secs; response 3 secs; fixation ITI 4.1 secs (3-7.5 secs)	3T GE Signa scanner	30	2000	90	220	3
(Falk et al., 2015)	Blocked. Blocks: initial suggestion (5 secs); reasons why/how (7 secs); brief reflection (6 secs); fixation 2.5 secs;	3T GE Signa scanner	30	2000	90	220	3

	every 7th block contained a longer block (12 secs).						
(Gearhardt et al., 2014)	Blocked. 'Myth busters' video; commercial breaks (10 trials) 2 mins 30 secs; commercials 15 secs. Total task 34 mins	3T Siemens Allegra scanner	30	2000	80	Detail not provided	4
(Jasinska et al., 2012)	Blocked. Blocks 24 secs (5 trials); fixation 7 secs (4-10 secs).	3T GE Signa Excite 2 scanner	30	2000	90	220	3
(Langleben et al., 2009)	Blocked. Fixation ISI 6 secs. Total task 10 mins 42 secs.	3T Siemens Trio scanner	30	3000	Detail not provided	220	3
(Newman-Norlund et al., 2014)	Blocked. Blocks 15 secs; 5 trials per block (2 secs); Fixation 1 sec; Rest blocks 15 secs. Total task 41 mins 36 secs.	3T Siemens Trio scanner	30	1950	75	?	3
(Vollstadt-Klein et al., 2011)	Blocked. 1 block 33 secs (5 trials); trials 6.6 secs; button response 9.9 secs; fixation >3.3 secs. Total task 15 mins.	1.5T Siemens Magnetom Vision scanner	60	0.6	90	220	4

(Wang et al., 2013)	Blocked. Initial fixation 16 secs; videos 30 secs; fixation ITI 16 secs. Total task 12 mins 36 secs.	3T Siemens Tim Trio scanner	30	2000	Detail not provided	220	3.4
(Wang et al., 2015)	Blocked. Trials 2 secs; blocks (6 trials); button response; fixation 10-13 secs. Total task 9.3 mins.	3T Siemens Tim Trio scanner	32	3000	Detail not provided	Detail not provided	Detail not provided

Abbreviations: T, tesla; TE, echo time; TR, repetition time

Appendix C

Study One: Functional MRI Acquisition Overview (continued)

Author, year	Template for normalisation	Smoothing filter	Analysis software
(Chua, Polk et al., 2009)	?	?	?
(Chua et al., 2009)	MNI152 template	5 mm FWHM	MCFLIRT program then SPM2
(Chua et al., 2011)	MNI152 template	5 mm FWHM	MCFLIRT program then SPM2
(Cooper et al., 2015)	MNI template	8 mm FWHM	SPM8
(Dinh-Williams, Mendrek, Bourque et al., 2014)	MNI standardised brain template	8 mm FWHM	SPM5
(Dinh-Williams, Mendrek, Dumais et al., 2014)	standardised ICBM152 brain template	8 mm FWHM	SPM5
(Do & Galvan, 2015)	standard MNI space	5 mm FWHM	FSL
(Enax et al., 2015)	MNI template	8 mm FWHM	SPM8
(E. B. Falk et al., 2011)	MNI standard stereotactic space	8 mm FWHM	FSL and SPM8
(E. B. Falk et al., 2016)	MNI template	8 mm FWHM	SPM8
(E. B. Falk et al., 2015)	MNI template	8 mm FWHM	AFNI and SPM8
(Gearhardt et al., 2014)	MNI T1 template brain ICBM152	6 mm FWHM	SPM8
(Jasinska et al., 2012)	MNI 152 template	7 mm FWHM	MCFLIRT then SPM

(Langleben et al., 2009)	MNI T1 template	6 mm FWHM	FEAT (FSL)
(Newman-Norlund et al., 2014)	DNP	8 mm FWHM	SPM8
(Vollstadt-Klein et al., 2011)	MNI EPI template	12 mm FWHM	SPM5
(Wang et al., 2013)	MNI T1 template	6 mm FWHM	Expert Analysis Tool (FSL) and MCFLIRT
(Wang et al., 2015)	MNI T1 template	5 mm FWHM	FEAT (FSL)

Abbreviations: AFNI, Analysis of Functional Neuroimages; EPI, echo planar imaging; FSL, FMRIB Software Library; FWHM, full width half maximum; ICBM, International Consortium for Brain Mapping; MNI, Montreal Neurological Institute; SPM, Statistical Parametric Mapping; T1, T1-weighted image

Appendix D

Study Two: Copy of Publication.

Original Paper

Brain Activation in Response to Personalized Behavioral and Physiological Feedback From Self-Monitoring Technology: Pilot Study

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Related Article:

This is a corrected version. See correction statement: http://www.jmir.org/2017/12/e430/

Abstract

Background: The recent surge in commercially available wearable technology has allowed real-time self-monitoring of behavior (eg, physical activity) and physiology (eg, glucose levels). However, there is limited neuroimaging work (ie, functional magnetic resonance imaging [fMRI]) to identify how people's brains respond to receiving this personalized health feedback and how this impacts subsequent behavior.

Objective: Identify regions of the brain activated and examine associations between activation and behavior.

Methods: This was a pilot study to assess physical activity, sedentary time, and glucose levels over 14 days in 33 adults (aged 30 to 60 years). Extracted accelerometry, inclinometry, and interstitial glucose data informed the construction of personalized feedback messages (eg, average number of steps per day). These messages were subsequently presented visually to participants during fMRI. Participant physical activity levels and sedentary time were assessed again for 8 days following exposure to this personalized feedback.

Results: Independent tests identified significant activations within the prefrontal cortex in response to glucose feedback compared with behavioral feedback ($P<.001$). Reductions in mean sedentary time (589.0 vs 560.0 minutes per day, $P=.014$) were observed. Activation in the subgyral area had a moderate correlation with minutes of moderate-to-vigorous physical activity ($r=0.392$, $P=.043$).

Conclusion: Presenting personalized glucose feedback resulted in significantly more brain activation when compared with behavior. Participants reduced time spent sedentary at follow-up. Research on deploying behavioral and physiological feedback warrants further investigation.

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KEYWORDS

functional magnetic resonance imaging; neuroimaging; physical activity; sedentary behavior; interstitial glucose

Appendix E

Study Two: Education Booklet.

Education Booklet

This booklet aims to provide you with some information about moderate-to-vigorous physical activity (MVPA), light physical activity (light PA), sedentary behaviour (sitting), and glucose levels. It contains information that will explain what each of these topics are, recommendations to maintain a healthy lifestyle and how a person could achieve these recommendations.

Contents

- Moderate-to-vigorous physical activity (MVPA)
- Light physical activity (light PA)
- Sedentary behaviour (sitting)
- Glucose levels

Loughborough University

National Centre for Sport & Exercise Medicine
Working for Health & Wellbeing

Moderate-to-vigorous physical activity (MVPA)

Activity monitor

Moderate-to-vigorous physical activity (MVPA) is considered effortful. It increases a person's heart rate, breathing rate and causes sweating.

- Doing more MVPA each week results in better health outcomes (more so than light physical activity)
- The Department of Health recommends that individuals achieve 150 minutes of MVPA per week
- 150 minutes should be achieved in bouts of MVPA lasting 10 or more minutes (continuously maintained at MVPA intensity)

How do I achieve this?

Activities which are considered moderate-to-vigorous are of a higher intensity than light activities. This means they will be done with a bit more effort (e.g. increased speed). You could go for a brisk walk, do some housework chores, jog in a nearby park, carry your shopping and/or attend a local gym.

Light physical activity (light PA)

Activity monitor

In contrast to MVPA, light PA may not cause breathlessness or sweating. However, light intensity activities such as standing or walking with minimal effort do offer health benefits.

- Doing more light PA each day results in better health outcomes
- It is recommended that individuals achieve at least 10,000 steps a day

How do I achieve this?

You could go for a walk in the morning, during the working day (e.g. lunch time or walking meetings) or in the evening. You could also use the stairs rather than the escalator or park further away from the supermarket entrance.

You could also try and stand more often by doing the washing up in multiple sessions, during TV advertisement breaks or whilst waiting for your bus at the bus stop.

Sedentary behaviour (sitting)

Sit-o-metre

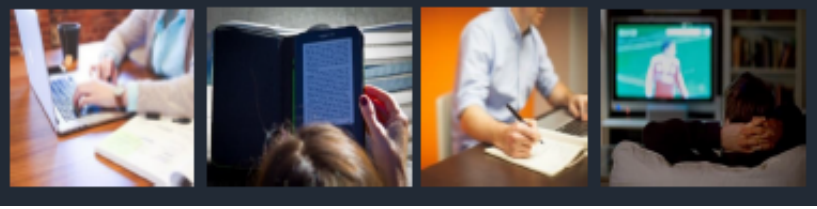
If people are not doing either MVPA or light PA, they are doing sedentary behaviour. Sedentary behaviour involves sitting or lying down (not sleeping) with little or no bodily movement.

- The Department of Health recommend that individuals minimise their time spent sedentary
- People should try and keep their total sedentary time to no more than 4 hours per day
- It is recommended that individuals regularly break up their sitting every 30 minutes

How do I achieve this?

At work, you could go and talk to a colleague instead of sending an email, re-locate items away from a desk (e.g. printers/bins) or collect items from somewhere in multiple trips.

At home, you could try and stand during television commercials, whilst on the telephone, whilst the kettle boils, whilst waiting for the toaster or you could split your laundry chores (e.g. ironing) into multiple parts.

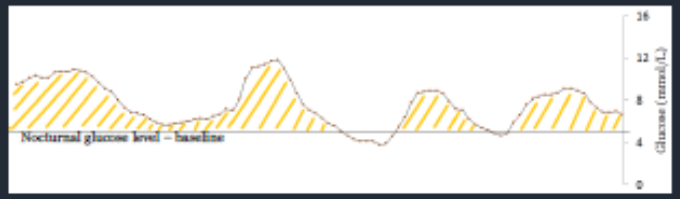


Glucose levels (sugar levels)

Behaviour, whether it is MVPA, light PA or sedentary, impacts health over time. One physiological or 'health' marker shown to be influenced by behaviour is glucose (sugar) levels. This is the amount of glucose or sugar present in the blood at a given time.

- Everyone has glucose in their blood all of the time; regardless of whether they are non-diabetic or diabetic
- Glucose levels can change because of food intake and physical activity. Once eaten, food is changed into glucose (sugar) which passes into the blood and results in an increase in glucose levels
- Glucose provides energy for the body to live and grow

- Target glucose level: 5 mmol/L (between 4.4 and 6.1 mmol/L)
- 'Area under the curve' (AUC) represents the total exposure or amount of glucose present in the blood over a set period of time on a graph (see graph below)
- The quicker a person's glucose returns to normal, the lower the AUC and the better controlled a person's glucose is



The AUC is identified by the orange lines in the above graph; notice that the AUC is quite large in this case. Also, there are 4 peaks caused by food intake.

Glucose levels (sugar levels)

- Consistently high glucose levels above the target range can result in pre-diabetes or diabetes. Generally speaking, non-diabetic individuals do not experience too many high glucose events
- People should aim to minimise the number of high glucose events and remain in the target glucose range
- HbA1c is a marker of diabetes risk and provides an average glucose value for the preceding 3 months. HbA1c (a marker of diabetes risk) measures the amount of glucose that is being carried by the red blood cells in the body
- Target HbA1c (a marker of diabetes risk): less than 6%

How do I achieve this?

Try and do light PA or MVPA before or after a meal to help glucose levels return to the target range.

Regardless of time of day, in order to take more glucose out of the blood, muscles need to be used. Muscles are activated when doing light PA and MVPA.

Notes


Activity monitor


Sit-o-metre


Glucose sensor


Activity monitor


Sit-o-metre


Glucose sensor

If you have any questions relating to the information provided in this Education Booklet then please do get in touch.

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Appendix F

Study Three: Copy of Publication.

BMJ Open

Sensing interstitial glucose to nudge active lifestyles (SIGNAL): feasibility of combining novel self-monitoring technologies for persuasive behaviour change

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ABSTRACT

Introduction Increasing physical activity (PA) reduces the risk of developing diabetes, highlighting the role of preventive medicine approaches. Changing lifestyle behaviours is difficult and is often predicated on the assumption that individuals are willing to change their lifestyles today to reduce the risk of developing disease years or even decades later. The self-monitoring technologies tested in this study will present PA feedback in real time, parallel with acute physiological data. Presenting the immediate health benefits of being more physically active may help enact change by observing the immediate consequences of that behaviour. The present study aims to assess user engagement with the self-monitoring technologies in individuals at moderate-to-high risk of developing type 2 diabetes.

Methods and analysis 45 individuals with a moderate-to-high risk, aged ≥40 years old and using a compatible smartphone, will be invited to take part in a 7-week protocol. Following 1 week of baseline measurements, participants will be randomised into one of three groups: group 1— glucose feedback followed by biobehavioural feedback (glucose plus PA); group 2—PA feedback followed by biobehavioural feedback; group 3—biobehavioural feedback. A PA monitor and a flash glucose monitor will be deployed during the intervention. Participants will wear both devices throughout the intervention but blinded to feedback depending on group allocation. The primary outcome is the level of participant engagement and will be assessed by device use and smartphone usage. Feasibility will be assessed by the practicality of the technology and screening for diabetes risk. Semistructured interviews will be conducted to explore participant experiences using the technologies.

Trial registration number ISRCTN17545949. Registered on 15/05/2017.

Strengths and limitations of this study

- ► The study will present real-time biological and behavioural information to participants using wearable technologies; a novel concept which has not been used in physical activity research.
- ► The study will be the first to deploy flash glucose monitors to people at risk of developing type 2 diabetes.
- ► A validated survey will be used to identify individuals at moderate-to-high risk of developing type 2 diabetes, among which we expect a proportion to have pre-diabetes.
- ► While the duration of the intervention (six continuous weeks) will permit the examination of change in engagement over time, the absence of additional follow-ups prevents the assessment of long-term use engagement and behaviour change maintenance.
- ► Cost-effectiveness analysis will not be undertaken in this study.

INTRODUCTION

There is widespread concern regarding the increasing prevalence of non-communicable diseases such as type 2 diabetes.[1] Type 2 diabetes currently imposes an annual cost of £23.7 bn through its associated complications[2]; however, this cost is likely to rise as it is projected to directly impact 592 million individuals worldwide by 2035.[3] Another imposing challenge is the proportion of the population living with undiagnosed diabetes (current prevalence estimated at 45.8%)[4]; which is possibly, in part, attributable to its asymptomatic state prior to the presentation of complications. Regardless of diagnosis status, preventing the development of type 2 diabetes is an international priority moving forward.[5] Pre-diabetes, categorised as either impaired fasting glucose or impaired glucose tolerance represents abnormal glucose homoeostasis and is placed between diabetes and normal regulation. Impaired fasting glucose has been defined as elevated fasting plasma glucose (100–126 mg/dL) while impaired glucose tolerance is

SIGNAL Protocol

Whelan ME, Kingsnorth AP, Orme MW, Sherar LB, Esliger DE. Sensing interstitial glucose to nudge active lifestyles (SIGNAL): feasibility of combining novel self-monitoring technologies for persuasive behaviour change. *BMJ Open.* 2017;7**:**e018282.

Original publication has been adapted to fit within this thesis.

Introduction

There is widespread concern regarding the increasing prevalence of chronic diseases such as type 2 diabetes (World Health Organization, 2014). Type 2 diabetes currently imposes an annual cost of £23.7bn through its associated complications (Hex et al., 2012); however, this cost is likely to rise as it is projected to directly impact 592 million individuals worldwide by 2035 (Guariguata et al., 2014). Another imposing challenge is the proportion of the population living with undiagnosed diabetes (current prevalence estimated at 45.8%) (Beagley et al., 2014); which is, in part, attributable to its asymptomatic state prior to the presentation of complications. Regardless of diagnosis status, preventing the development of type 2 diabetes is an international priority moving forward (Barry et al., 2017). Prediabetes, categorised as either impaired fasting glucose or impaired glucose tolerance represents abnormal glucose homeostasis and is placed between diabetes and normal regulation. Impaired fasting glucose has been defined as elevated fasting plasma glucose (100-126 mg/dl) whilst impaired glucose tolerance is characterised by an elevated two hour plasma glucose concentration (140-199 mg/dl) following intake of a 75g glucose load (Genuth et al., 2003). One in seven adults have impaired glucose regulation (Diabetes UK, 2006) and, compared to individuals living with normal circulating glucose levels, pre-diabetics are five to ten times more likely to develop type 2 diabetes (Santaguida et al., 2005) with 5-10% of people becoming diabetic annually (Forouhi et al., 2007). Diabetes is projected to be one of ten leading causes of death worldwide (Tabák et al., 2012); thus, identification and prevention are crucial for early intervention. A lack of physical activity is considered one of the major risk factors for chronic disease and is comparable to the ill-effects of obesity (Olshansky et al., 2005) and smoking (National Research Council Committee on Population, 2011) individually. Given that physical inactivity, where insufficient levels of physical activity are achieved, is attributed to an estimated 7% of type 2 diabetes cases (Lee et al., 2012), it is an important modifiable lifestyle behaviour to target. With the prevalence of impaired fasting glucose doubling in individuals at 40-59 years and remaining consistent beyond 60 years (Cowie et al., 2009), targeting efforts toward specific

age cohorts is crucial. Individuals with abnormal glucose homeostasis are referred onto community-based lifestyle behaviour programmes such as The Healthier You: National Diabetes Prevention Programme (NDPP). Initiated in 2016, the programme aims to roll out nationally by 2020 as part of the NHS Five Year Forward plan (NHS England, 2016). The present study intends to implement a community screening approach, monitor participant retention and to investigate whether digital health technologies providing feedback about physical activity and glucose levels may play a role in the prevention pathway (which may be amenable to the NDPP framework).

With increasing recognition toward the integration of technology into usual care pathways (i.e. emergence of NHS Digital), it is a crucial time to consider how technologies could contribute to the management of chronic diseases. Given recent consumer interest (Ferguson et al., 2015), wearable technologies allow people to self-monitor behaviour and health. Gardner and colleagues reviewed behavioural interventions and identified self-monitoring of behaviour as a particularly promising behaviour change technique (Gardner et al., 2016). Similarly, continuous glucose monitoring technology has shown promise for longer-term physiological outcomes (including glycated haemoglobin [HbA1c]) (Vigersky et al., 2012); supporting the suggestion that more frequent engagement leads to better health outcomes (Fonda et al., 2013). Self-monitoring of both behaviour and outcomes are listed within the taxonomy alongside 91 other ingredients (including feedback and goal-setting) in behavioural interventions (Michie et al., 2013). As well as delivering key behaviour change techniques, digital health technologies also support Control Theory (Carver et al., 1982). More specifically, people are presented with information about a present state via feedback (e.g. 9,000 steps) and are often provided a set goal to achieve (i.e. 10,000 steps). Equipped with this information, people may make efforts to achieve the goal or desired outcome (i.e. ≥10,000 steps) because they have been informed how they are performing relative to it. The majority of research to date has focused on the deployment of technologies to self-monitor movement behaviours (e.g. Cadmus-Bertram et al., 2015) or specific health markers (e.g. Polonsky & Fisher, 2013) in isolation. Although these approaches have shown to be beneficial to behaviour change in the short term, most user engagement is not sustained beyond six months (Ledger et al., 2014). Despite research conducted on short-term improvements, it is not yet clear whether results are sustained with prolonged use (Barwais et al., 2013; Tudor-Locke & Lutes, 2009). However, the rationale is that when provided with information about their current levels of activity, people may feel motivated to improve their behaviour.

With a view to sustaining the 'honeymoon period' of technology-bolstered behaviour change, a logical next step would be to deploy wearable technologies in combination. For example, studies investigating the acute effects of brief physical activity bouts or interruptions to prolonged sedentary behaviour on glucose levels in controlled settings have found reductions in postprandial glucose as a result of increased movement (e.g. DiPietro et al., 2013; Dunstan et al., 2012; Peddie et al., 2013; Reynolds et al., 2016). As a result, the present study proposes that delivering behavioural and physiological feedback in parallel may be more persuasive rather than feedback delivered in isolation. This approach may offer a platform for people to self-educate themselves about the relationship between movement and acute health status (i.e. walking after a meal leads to marked reductions in glucose levels); which may help sustain engagement with digital health technologies. With ongoing developments, technologies such as flash glucose monitoring offer a wealth of information to users without the need for invasive fingerprick samples; offering a useful tool for non-diabetic individuals (who are not accustomed to regular fingerprick blood samples) (Bailey et al., 2015). To date, an important limitation of the efforts to encourage people to be more physically active has been the assumption that we are willing to change our lifestyles *today* to reduce our risk of developing disease *years or even decades later*. Implementing specific behaviour change techniques such as self-monitoring, goal-setting and feedback (Michie et al., 2013), wearable devices could empower individuals to manage their health through a change in behaviour by recognising movement patterns and observing influences on health. Building on previous findings which observed greater levels of brain activation in response to personalised glucose related information (over behavioural information) (Whelan et al., 2017; Chapter Three), the present study aims to examine the role of providing novel digital health technologies presenting bio-behavioural feedback in those living at moderate-to-high risk of type 2 diabetes.

Aims and Objectives

Primary aim

The primary aim of this study is to investigate participant engagement using self-monitoring technologies for physical activity and glucose.

Secondary aims

The secondary aims of this study are to explore (i) the feasibility of the intervention trial at baseline, 1, 2, 3, 4, 5, and 6 weeks; (ii) levels of physical activity and interstitial glucose levels at baseline, 1, 2, 3, 4, 5, and 6 weeks and (iii) levels of technology readiness, health literacy, health status and attitudes towards one's own health at baseline and post self-monitoring.

Methods

Study setting

Participants will be recruited from the community in Leicestershire, UK from May to August 2017. All appointments (three or four in total, depending on group allocation) will take place at the National Centre for Sport and Exercise Medicine at Loughborough University, UK.

Study design

The feasibility study protocol has been prepared in accordance with the Standard Protocol Items: Recommendations for Interventional Trials (SPIRIT) (Chan et al., 2013) with reference to the Template for Intervention Description and Replication (TIDieR) (Hoffmann et al., 2014).

The study will aim to recruit 45 individuals with 15 participants randomly allocated to each of the three groups. No specific sample size has been calculated due it's the feasibility nature of the study, but results will inform the development of a full-scale intervention.

Participant involvement in the Sensing Interstitial Glucose to Nudge Active Lifestyle study will last seven weeks. Following baseline (one week), participants will be randomised into one of three intervention groups. Participants will be notified of their group allocation at the second appointment before starting the intervention period (six weeks). Appointments will be arranged at the preceding appointment where possible. The study was registered on the International Standard Randomised Controlled Trial number (ISRCTN) Register (ISRCTN17545949) in May 2017.

Randomisation

Participants will be block randomised using a 1:1:1 study allocation ratio, coordinated by a remote internet-based service (http://www.sealedenvelope.com/). Randomisation will be done by a member of the research group, independent to the present study. Baseline measures will be conducted pre-randomisation. Participants will be notified of their group allocation at

appointment two. In the event of participants originating from the same household, identical group allocation will be employed to avoid any cross-contamination.

Inclusion criteria

Participants will be at least 40 years old, be at moderate-to-high risk of developing type 2 diabetes (Gray et al., 2010) and use a compatible Android smartphone.

Compatible smartphones at the time of the study will be defined as having the following characteristics: An Android operating system of 4.0 or higher, Near Field Communication (NFC), a screen resolution of 480x800 to 1080x1920 and a screen size of 8.9-14.5cm. Exceptions were the Samsung Galaxy 7, Samsung S8, Nexus 5X and Nexus 6P which cannot install the LibreLink application (app).

Exclusion criteria

Individuals with a clinical diagnosis of diabetes, a HbA1c of ≥6.5%, or have suspected/confirmed pregnancy will be excluded. Participants who are unable/unwilling to provide informed consent, cannot/unwilling to adhere to the study protocol or cannot read/write English will also be excluded.

Recruitment

Participants will be recruited at community sites through the distribution of posters and leaflets in community organisations and local businesses based in Leicestershire, UK. Individuals will also be recruited through existing participant databases. All individuals will be directed to complete a brief survey to determine level of risk for type 2 diabetes. The questions will be presented via an online survey platform (Qualtrics, Provo, UT) and will relate to sex, age, ethnic background, familial history of diabetes, waist circumference, body mass index and blood pressure. The validated survey has been used in studies applying risk score algorithms on primary care electronic data (Gray et al., 2012). Waist circumference will be replaced with clothing size and fit following guidance offered by Battram and colleagues (Battram et al., 2011). Moderate-to-high risk individuals will be contacted by the research team to take part in the study. Participant information sheets will be provided. Ineligible individuals (i.e. low risk, increased risk or a moderate/high risk, but are not aged at least 40 years old nor use an Android smartphone) will be directed to Diabetes UK ‘Type 2 diabetes: What to do if you’re at risk’ information booklets.

Study procedure

First appointment and baseline

An outline of the study procedure is presented in the next Figure. Appointment one will involve informed consent, health measures (height, weight, percentage body fat, waist circumference, blood pressure, HbA1c, grip strength, quadriceps strength and aerobic fitness; full methodological details are provided in the measures section below) and a brief demographics questionnaire. Participants will complete a physical activity readiness questionnaire for screening purposes before completing the aerobic fitness assessment (Warburton et al., 2011). Participants will be fitted with a waist-worn accelerometer and a wrist-worn activity tracker. Additional details are presented in Appendix G. Neither device will provide feedback to the participant during the seven consecutive days of wear (Appendix H). Participants will be asked to install two mobile apps onto a personal Android smartphone to comply with the number of technologies deployed (further details provided in Appendix I). Both smartphone apps will sit idle on the smartphone for the duration of baseline. Participants will be asked to sync the activity tracker via the smartphone app; switching on Wi-Fi and Bluetooth simultaneously at least once every five days for ≥1 hour to ensure the sync occurs.

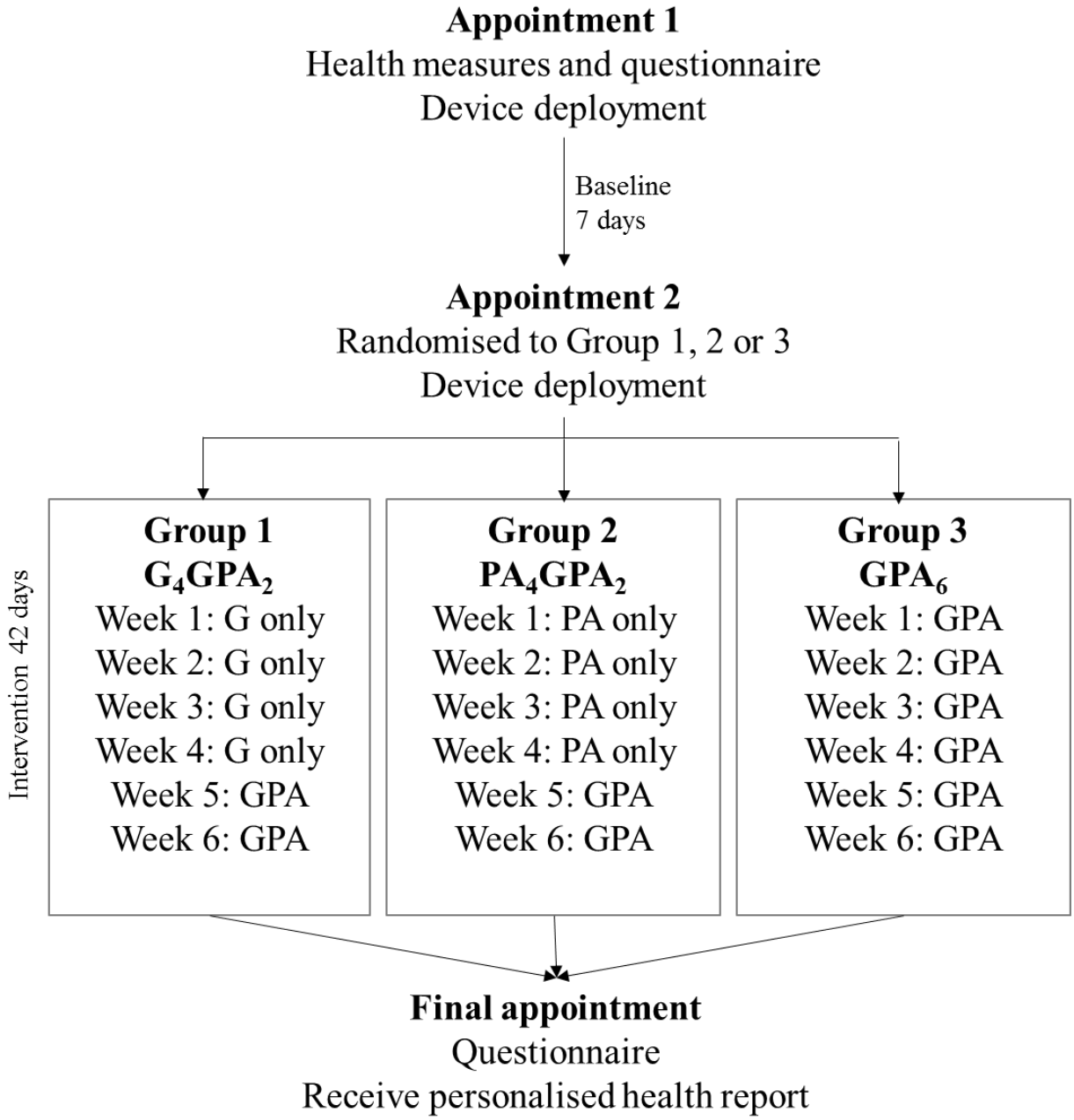


Figure. An outline of the study flow. G_4GPA_2 represents glucose feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks); PA_4GPA_2 represents physical activity feedback (4 weeks) followed by glucose and physical activity feedback (2 weeks) and GPA_6 represents glucose and physical activity feedback (6 weeks). Abbreviations: G, glucose feedback; PA, physical activity feedback; GPA, glucose plus physical activity feedback.

Second appointment and intervention

One week later (following baseline), participants will attend appointment two where they will be informed of their group allocation. Participants will be asked to complete a brief questionnaire, to continue wearing the activity tracker during the intervention (settings may or

may not be adjusted) and to return the accelerometer. A glucose sensor will be deployed to each participant to measure glucose levels. An instruction manual will be provided according to the participants' group allocations. Participants will be provided with additional supplies of glucose sensors to last for four (Groups 1 and 2) or six weeks (Group 3) of the intervention. Accounts for both the activity tracker and glucose sensor will be connected to Diasend (Diasend Inc., Chicago, IL). An overview of the three groups is provided below.

Group 1 (glucose feedback then glucose plus physical activity feedback, G_4GPA_2)

Glucose feedback will be presented to participants for four weeks via the LibreLink app (Abbott Diabetes Care Inc., Alameda, CA). Participants will install the LibreLink app (Abbott Diabetes Care Inc., Alameda, CA) onto a personal Android smartphone to interact with the Freestyle Libre via Near Field Communication for measurement of glucose. The glucose monitor has a lifespan that restricts wear to 14 consecutive days. The app will remind participants to scan every seven hours and to remove/replace after 14 days. The LibreLink app will continuously display the number of days left.

Group 2 (physical activity feedback then glucose plus physical activity feedback, PA_4GPA_2)

Physical activity feedback will be presented for four weeks via the Fitbit app. In contrast to G_4GPA_2, participants will not have the LibreLink app installed and so will not have access to glucose feedback. Participants will be informed that the glucose sensor is functional (recording data) and participants will be asked to remove and replace the expired sensor with another sensor after 14 days.

Device unmasking for G_4GPA_2 and PA_4GPA_2 after four weeks

At the end of the first four weeks of the intervention, participants in G_4GPA_2 and PA_4GPA_2 will attend a brief appointment (up to one hour in duration). For Group 1, the researcher will adjust settings to reveal physical activity feedback via the Fitbit app and device. For PA_4GPA_2, the researcher will install the LibreLink app to reveal glucose feedback. All participants will be able to access glucose plus physical activity feedback for the remaining two weeks of the intervention.

Group 3 (glucose plus physical activity feedback, GPA_6)

Participants in GPA_6 will receive glucose plus physical activity feedback for the full six weeks via the two independent LibreLink and Fitbit apps. Participants will install the LibreLink mobile app onto a personal Android smartphone to interact with the Freestyle Libre to measure

glucose. The app will remind participants to scan every seven hours and to remove/replace the sensor after 14 days.

Final appointment

All participants (G_4GPA_2, PA_4GPA_2 and GPA_6) will be asked to attend the final appointment at the end of the intervention where they will complete a questionnaire (identical to appointment 2, apart from the revised Diabetes Knowledge Test). All participants will also receive a personalised health report containing results from the health measures conducted at appointment one.

Device masking

All email accounts and password combinations will be manually generated and managed by the research team to prevent use of identifiable information. During baseline wear, the activity tracker will be physically masked using black tape applied to the screen; leaving only time and date viewable. Participants will be asked not to tamper with the screen; however, if they do manipulate the masking, it should be noticeable to the research team. Settings on the Fitbit app will also be adjusted to remove physical activity metrics from the device screen and notifications fully restricted on their phone and activity tracker (Appendix H). However, participants will not be locked out of the app due to the requirement to sync the device. Time spent on the Fitbit app will be inspected using Ethica Data (Kitchener, Ontario, Canada) to identify potential unauthorised use. The activity tracker will also be set to *all day sync* to minimise data loss with data automatically transferred (Wi-Fi and Bluetooth must both be simultaneously switched on). When required to prevent access to glucose feedback, participants will wear the glucose sensors for 14-day periods as normal but will not be asked to install the LibreLink app nor scan the sensor (i.e. no data will be collected). This will standardise wear across all three groups.

Data management and storage procedures

All data collected will be anonymised by assigning a participant ID. Accounts with the three apps (Fitbit, LibreLink and Ethica Health) will be setup using study-specific (‘dummy’) email addresses and passwords, accessible only to the research team, to minimise use of personalised information. All data will be stored securely on the Loughborough University server, as password protected, encrypted documents and original paperwork kept in locked storage. No directly personally identifiable information will be collected through these platforms. GPS

(global positioning system) will be collected via Ethica Data which could theoretically be 'reverse-engineered' to re-identify individuals; however, all participants will be explicitly informed about all information monitored as part of the study. For individuals who do not wish to have their location services monitored, we will set up a 'reduced access' version of Ethica Data (app usage, screen state and survey responses only).

Primary outcomes

User engagement

Time spent on the official free Fitbit and LibreLink apps will be quantified using Ethica Data as well as time-stamped data relating to when the smartphone screen was turned on and off. In combination, these two data sources will reveal the proportion of time that the devices' apps were used in relation to total smartphone use. These data will be recorded at either a day level (e.g. aggregate time) or event level (e.g. record of each time an app was opened) depending on the Android smartphone model. How often and how much time spent on the two apps compared with other apps on participants' smartphones will also be quantified. Number of times the activity tracker syncs (occurs when the app is opened, assumed to see feedback about physical activity) and scans of the glucose sensor (occurs when the participant scans and to see feedback about glucose levels) will also be recorded. *Compulsory engagement* will be participants having to sync the activity tracker at least once every five days and scan the glucose sensors at least once every seven hours. The number of syncs and scans recorded above *compulsory engagement* will reflect *optional engagement*. Identifying when and how often syncs and scans happen and how these patterns change over the course of the intervention (from week one to six) will indicate engagement with the technology. We will also identify if participants change the goal settings relating to steps, floors climbed and active minutes on the Fitbit app. These settings will be checked daily between the hours of 18:00-19:00 by the research team and changes will be flagged with details of the original and new setting logged. In addition, assessing whether participants responded to prompts offered by the activity tracker will also be conducted (i.e. did participants achieve 250 steps/hour? See Behaviour Change Techniques section for further detail).

Remote monitoring of participant glucose and physical activity will be completed using Diasend (Diasend Inc., Chicago, IL) and Fitabase (Small Steps Labs LLC., San Diego, CA), respectively. Diasend will connect with the Freestyle Libre via the LibreLink app and data will be recorded and accessed through this software. Additional data sources to be monitored by

Ethica Data include battery status (i.e. smartphone plugged in? Charging?), Bluetooth and Wi-Fi (turned on or off). Quantifying these data sources will provide valuable insight into participant behaviour (e.g. do participants only use Wi-Fi and Bluetooth for the purpose of our intervention? Are participants charging it more often in the intervention compared with baseline?). Ethica Data will also monitor location (GPS), motion (pedometer, accelerometer, gravity, gyroscope, linear acceleration, magnetic field, orientation) and survey responses. These digital streams will monitor smartphone usage and will provide detailed data on human behaviour during a free-living, naturalistic setting. In total, fourteen data sources will be monitored. In the event a participant raises concerns relating to the number and/or type of data sources being monitored, a *restricted* coverage option of only three data sources (app usage, screen state and survey responses) will be offered.

Secondary Outcomes

Feasibility

The feasibility of deploying novel self-monitoring technologies in parallel was structured around the guidelines by Bowen and colleagues (Bowen et al., 2009; see Table). Practicality and acceptability will be the two components focused on in the present study. Practicality and acceptability each have several indicators that will be used to assess the feasibility of deploying self-monitoring technologies.

Table. An outline of the feasibility components

Feasibility component	Data source (indicator of feasibility)
Practicality of technology/intervention	• Fitabase (sync compliance, missing data and response to haptic prompt) • LibreLinkUp (scan compliance) • Diasend (missing data, identification of Freestyle Libre sensor-related issues) • Project records (identification of need to dispatch additional Freestyle Libre sensors, number of individuals screened, rate of eligibility, study uptake and retention)
Acceptability of technology/intervention	• Fitabase (Fitbit wear time) • Diasend (Freestyle Libre wear time, digital footprint of time taken to move onto the next Freestyle Libre sensor i.e. sensor delay) • Project records (changes to goal settings, manual withdrawals, appointment attendance, retention to follow-up) • Ethica Data (digital footprint of app usage, Bluetooth and Wi-Fi status, battery status, electronic withdrawal)

[a]*Full coverage: app usage, screen state, Bluetooth, Wi-Fi, GPS, pedometer, accelerometer, gravity, gyroscope, linear acceleration, magnetic field, orientation, battery and survey responses.* [b]*Restricted coverage: app usage, screen state and (exit) survey only.*

Withdrawal

If a participant decides to withdraw from the study at any time prior to the final appointment, they will be able to leave the study via (i) the Ethica Health app on their personal smartphone (aligning with a dynamic consenting process [Teare et al., 2015]) or by (ii) contacting the research team via telephone or email. Participants that decide to withdraw via Ethica Health will be directed to complete a brief exit survey on the app. The research team will contact all participants for an optional exit interview (5-10 minutes) via telephone. This will be recorded using Tapeacall (http://www.tapeacall.com/) and will explore reasons for not completing the study.

Physical activity levels

ActiGraph

In an effort to determine the physical activity levels of the participants relative to general population, participants will be asked to wear an ActiGraph wGT3X-BT accelerometer (ActiGraph, Pensacola, FL; see Figure) for seven days during waking hours and to remove for any water-based activities (e.g. showering and swimming). The waist-worn (i.e. over the right hip, mid-clavicular line) ActiGraph will quantify time spent sedentary, in light and moderate-to-vigorous physical activity as well as daily step counts and will function as a data logger (i.e. no feedback). ActiGraph accelerometers have been validated (Melanson Jr & Freedson, 1995; Plasqui & Westerterp, 2007) and extensively deployed (Chaudhury & Esliger, 2008; Hagströmer, Oja, & Sjöström, 2007; Troiano et al., 2008) to measure physical activity under free-living conditions. Data from the ActiGraph will be collected at 100 Hz and integrated into 60 second epochs using ActiLife (ActiGraph, Pensacola, FL) and processed using Kinesoft (Kinesoft, Loughborough, UK). Non-wear will be defined as 60 minutes of consecutive zeros (allowing for up to two minutes of interruptions) with a minimum wear of 10 hours used to define a valid day (Troiano et al., 2008). A minimum of 4 valid days will be used to define a valid file with sedentary time classified as <100 cpm, light activity as 100-2019 cpm and MVPA as ≥2020 cpm (Troiano et al., 2008).

Figure. Images of the ActiGraph (left), Fitbit Charge 2 (middle) and Freestyle Libre (right)

Fitbit

The Fitbit Charge 2 (Fitbit Inc., San Francisco, CA) will be worn on the non-dominant wrist and, whilst being sweat, rain and splash proof, participants will be asked to remove the device for water-based activities. The Fitbit records intensity (i.e. minutes spent lightly active, fairly active and very active) in addition to heart rate and step count (see Figure). Heart rate will be assessed using Fitbit's proprietary PurePulse optical heart rate technology. To examine changes in physical activity over the study duration, participants will be requested to wear the device for the full seven weeks and data will be analysed in 60 second epochs following export from

Fitabase. Previous models of the Fitbit have been validated for step count (Lee et al., 2014). A waking protocol will be implemented with non-wear defined as a loss of a heart rate signal. Participants will be requested to sync the Fitbit at least once every five days (rather than the company recommendations of seven days) to minimise data loss. Syncs beyond seven days will result in day level data rather than minute level data. These syncs will either occur automatically (i.e. without the app open) or will be user-driven (i.e. with the app open) depending on how the *all-day sync* is set, and heart rate will be set to automatic (only record heart rate when device is worn).

Glucose levels

Freestyle Libre

The minimally-invasive Freestyle Libre flash glucose monitor (Abbott Diabetes Care, Alameda, CA) will be covered with Tegaderm (3M Health Care, St. Paul, MN) to help maintain position and adhesion during the 14-day sensor lifespan. Three strips of Tegaderm will be provided to participants per sensor to allow for replacement when the Tegaderm becomes dirty. Participants will be asked to wear the device continuously without removal for water-based activities (see Figure). The Freestyle Libre demonstrates consistent accuracy throughout the 14 days with a mean absolute relative difference of 11.4% compared with capillary blood glucose, a lag time of 4.5-4.8 minutes and is not impacted by physical characteristics including age, BMI and HbA1c (Bailey et al., 2015). Participants will be requested to scan the glucose monitor at least once every seven to eight hours to minimise data loss. If participants experience skin irritation on the non-dominant arm in the region of app, participants will be advised to switch to their dominant arm. Interstitial glucose data will be downloaded in 15-minute epochs using Diasend, an online platform connected to the LibreLink app. Participant accounts will be linked to Diasend from the point of LibreLink app installation. The next Figure illustrates how the numerous components connect to achieve the primary and secondary aims.

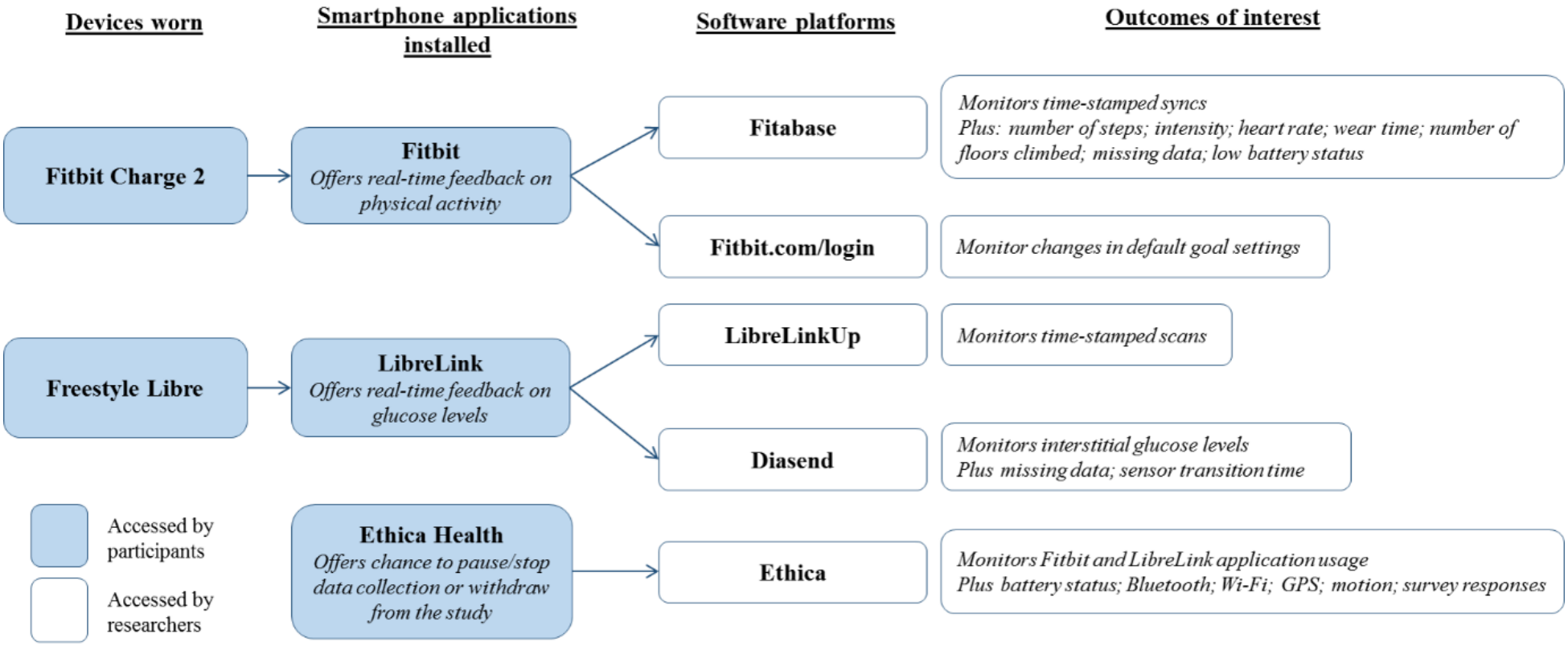


Figure. A schematic of how the technologies and platforms connected together

Levels of technology readiness, health status and attitude

All questionnaires will be completed electronically using an online platform for immediate data entry (http://www.onlinesurveys.ac.uk/; Bristol, UK). At appointment two, quality of life will be assessed via the 26 item EQ-5D-5L (Herdman et al., 2011), technology readiness via the 16 item Technology Readiness Index (TRI 2.0) (Parasuraman & Colby, 2015), health literacy via the 8 item eHealth Literacy Scale (e-HEALs) (Norman et al., 2006), diabetes knowledge via the 20 item revised diabetes knowledge test (Collins et al., 2011) and general attitude toward developing diabetes via the 8 item general attitudes section of the Risk Perception Survey for Developing Diabetes (RPS-DD) (Walker et al., 2003).

Other measures

Participant Characteristics

Self-reported age, sex, ethnic background, employment, household income, postcode (to provide an Index of Multiple Deprivation [IMD] score) and education will be recorded. Participants will be asked to provide these details at appointment 1.

Health, physical functioning and fitness

HbA1c will be assessed at the first appointment using an Afinion AS100 point-of-care system (Alere Inc., Waltham, MA). Results will be processed following collection and samples disposed of immediately. Participants receiving a result ≥6.5% will be ineligible, readings of 6-6.4% classified as pre-diabetic (National Institute for Health and Clinical Excellence, 2012) and readings of <6% classified as euglycemic. A measure of height will be conducted using a Seca stadiometer (Seca, Hamburg, Germany) and weight and body fat percentage measured using Tanita scales (Tokyo, Japan). Participants will be asked to remove their shoes and socks prior to these measurements. Two measures of waist circumference will be taken at the midpoint between the lowest rib and top of the iliac crest; if the difference ≥1cm, the two measurements will be repeated (World Health Organization, 2011b). Three measures of resting blood pressure will be recorded using an Omron digital monitor (Omron Corporation, Kyoto, Japan) with the first measure taken after the participant has remained seated for ≥10 minutes. A rest period will be enforced between each of the three measurements.

Grip strength will be assessed using a handheld Takei dynamometer (Takei Scientific Instruments, Tokyo, Japan) whilst standing with hands positioned down each side. Participants will be asked to completed three trials on each hand with brief pauses in between to minimise

muscle fatigue (Canadian Society for Exercise Physiology, 2004). Quadriceps strength will be assessed using the DAVID G200 knee extension machine (David Health Solutions Ltd., Helsinki, Finland). Aerobic fitness will be assessed using the modified Canadian Aerobic Fitness Test (mCAFT) (Canadian Society for Exercise Physiology, 2004). The mCAFT is a sub-maximal step-test protocol with participants instructed to complete ≥1 three-minute stages of stepping at a speed dictated by an audio track. Heart rate will be monitored throughout with the stepping stages continued until heart rate ≥85% of age-predicted maximal heart rate. Participants' scores for aerobic fitness will be defined according to the following formula*:* 10*[17.2 + (1.29 x oxygen cost at the final stage) - (0.09 x weight in kg) - (0.18 x age in years)] (Canadian Society for Exercise Physiology, 2004).

Behaviour change techniques

Prior to starting the intervention, the researcher will implement the default settings for levels of physical activity (BCT 1.1: Goal setting [behaviour]) (i.e. 10,000 steps and 10 floors climbed) and glucose (BCT 1.3: Goal setting [outcome]) (i.e. 4.0-5.9 mmol/L). Participants will be fully informed that they can freely change the goals set for physical activity as preferred (i.e. should the default value be too easy/difficult) via the Fitbit app. However, participants will be advised to not make any changes via the LibreLink app for the target glucose range. Attainment of a goal will be assessed as either complete or incomplete. Participants will be asked to sync the Fitbit (at least once every five days) and scan the Freestyle Libre (at least once every seven to eight hours) if they are in the respective group to receive feedback from these devices. This action has a dual purpose; to minimise data loss and to encourage continued engagement with the technologies. Participants will also receive haptic feedback (BCT 7.1: Prompts/cues; i.e. a gentle vibration) as a reminder to move by the Fitbit 10 minutes prior to the end of each hour (default 09:00-18:00) if 250 steps have not been taken. The reminder to move prompt aims to encourage interruptions in prolonged sedentary bouts as is recommended by the UK physical activity guidelines (UK Department of Health, 2011b). In relation to the other behaviour change techniques, participants will be able to monitor physical activity levels using the Fitbit Charge 2 (BCT: 2.3 Self-monitoring of behaviour) and glucose levels using the Freestyle Libre (BCT: 2.4: Self-monitoring of outcome(s) of behaviour) which is a minimally-invasive device that presents feedback about glucose (BCT: Biofeedback).

Data analysis

Analysis of primary outcomes

Ethica Data is a fee-for-service platform that will be used to provide time-stamped data relating to app usage. This is an app installed on participants' phones and sits idle during the study period. The number of scans and syncs will be unobtrusively assessed using the free LibreLinkUp app (Abbott Diabetes Care Inc., Alameda, CA) and Fitabase (Small Steps Labs LLC., San Diego, CA), respectively. Fitabase is a fee-for-service platform that permits access to download 60 sec epoch Fitbit data (i.e. levels of physical activity) and remote monitoring of Fitbit devices (e.g. battery level and time since last sync event) via Bluetooth and Wi-Fi. Identification of moments where participants have decided to change the goal settings will be completed by accessing the online Fitbit account. The researchers will remotely access participants' accounts daily between 18:00-19:00 to note goal settings; recording the date and previous/current settings for all metrics (e.g. step count) to help identify any changes.

Analysis of secondary outcomes

To assess eligibility, uptake and retention, we will monitor how many individuals complete the screening survey, how many meet our inclusion criteria and of these how many decide to enrol. In addition, the screening survey will also identify recruitment sources. Identifying non-usage attrition and dropout attribution is crucial to assess the feasibility of an intervention as they are both important but distinct constructs (Alkhaldi et al., 2016). Non-usage attrition, where participants have disengaged from the intervention but have not dropped out, will be defined as participants who attend appointment two but do not sync the Fitbit or scan the Freestyle Libre. Dropout attrition will be defined as participants who explicitly withdraw from the study via Ethica Health or direct contact with the research team. The number of participants who enrol into the full coverage (all 14 data sources monitored) or restricted coverage (only three data sources monitored) for Ethica Data will also be recorded. Diasend is a fee-for-service platform that permits access to download 15-min epoch data from the Freestyle Libre and remote monitoring of multiple LibreLink accounts. Descriptive statistics of the sample will be conducted. In addition, two-way repeated measures ANCOVAs will be conducted to assess changes in engagement (dependent) according to group (independent) having adjusted for participant characteristics. Similarly, two-way repeated measures ANCOVAs will be conducted to assess changes in physical activity (dependent) according to group (independent)

having adjusted for Fitbit wear time. All data will be analysed using Statistical Package for Social Sciences (SPSS Inc. Chicago, IL).

Dissemination

The present study aims to consider whether these technologies may have potential use in existing pre-clinical care pathways; how engaging with self-monitoring technologies (providing glucose plus physical activity feedback in combination) may positively influence rates of uptake, adherence, retention and behaviour change. This line of research will inform the development a full-scale randomised-controlled trial. We will publicise study findings online, present them at international conferences relating to diabetes, physical activity and digital health and publish via peer-reviewed journals.

Appendix G

Study Three: An outline of device deployment decisions.

An outline of the data collection procedures for the three wearable technologies deployed.

	ActiGraph (wGT3x-BT)	Fitbit (Charge 2)	Abbott (Freestyle Libre)
Devices	24 devices used	45 devices used	157 devices used 0 handheld readers used
Sample rate	100 Hz (.gt3x file format)	60 seconds	900 seconds
Epoch	60 seconds	60 seconds	900 seconds
Initialisation	Deployed in delay mode on day 0. Commenced logging on day 1 at 00:00:00; stop time applied 7 days after	Commenced logging data at point of initialisation on day 0	Commence logging data 1 hour after point of initialisation on day 8 (Groups 1 and 3) or day 29 (Group 2) and after any additional sensor applicationapps
Deployment	Fitted by participant (on day 0) with guidance from researcher	Fitted by participant (on day 0) with guidance from researcher	Fitted on day 8 by participant (using step-by-step instructions and guidance from research team) to inform subsequent self-deployment of sensors
Location	Anterior hip, mid-line of the right thigh	Non-dominant wrist	Upper portion, non-dominant posterior brachium
Wear duration	Baseline: 7 days (10,080 epochs) Intervention: Not worn	Baseline: 7 days (10,080 epochs) Intervention: 42 days (60,480 epochs)	Baseline: Not worn Intervention: 42 days (60,480 epochs)
Wear instructions	Continual wear except for sleep and water-based activities	Continual wear except for sleep and water-based activities	Continual wear (24hr) with adhesive tape over sensor
Charging	Not required	Requested to charge overnight every day	Not required
Non-wear	≥60 min of consecutive zeros with allowance for 2 minutes of interruptions coded as non-wear.	An absence of heart rate signal.	Duration of sensor (up to 14 days) and classify missing data between sensors.
Valid day criteria	≥10 hours of valid waking wear time	≥10 hours of valid waking wear time	≥90% of data points per day
Valid file	Baseline: ≥4 valid days (baseline) Intervention: Not applicable	Baseline: ≥4 valid days Intervention: ≥24 valid days	Baseline: Not applicable Intervention: ≥4 days

Appendix H

Study Three: Standard operating procedure for the Fitbit.

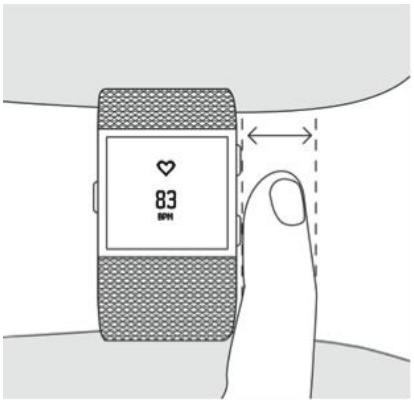
Masking the Fitbit Charge 2

General

Tape over the whole screen on the device itself but reveal date and time.

Inform of syncing protocol (Bluetooth and Wi-Fi ON simultaneously for at least 30 minutes)

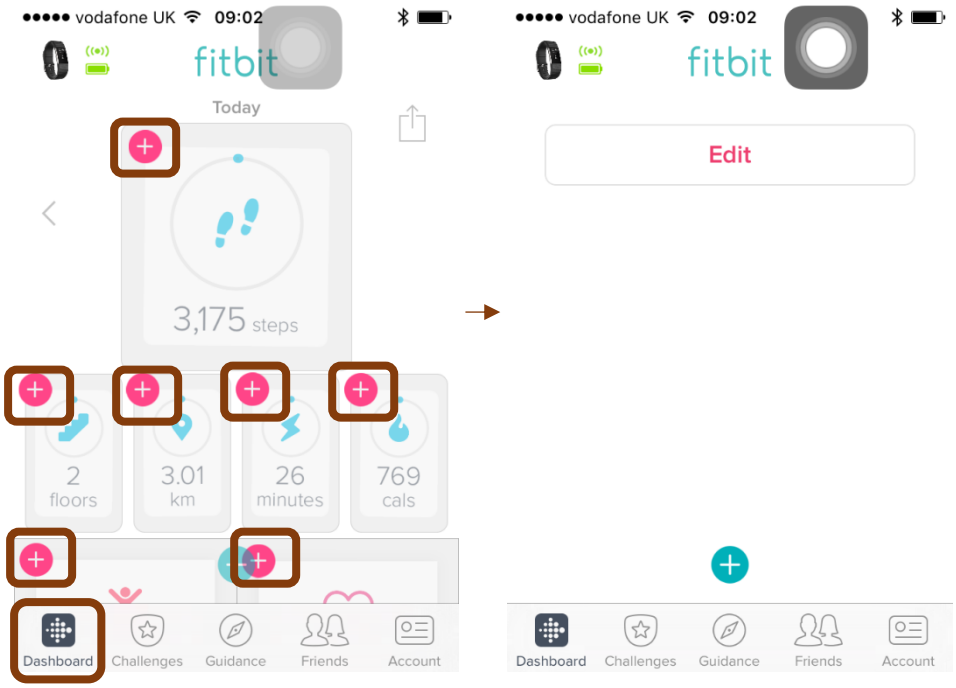
Once completed the following process, check that the device is updated (i.e. only shows floors)



Official Fitbit app

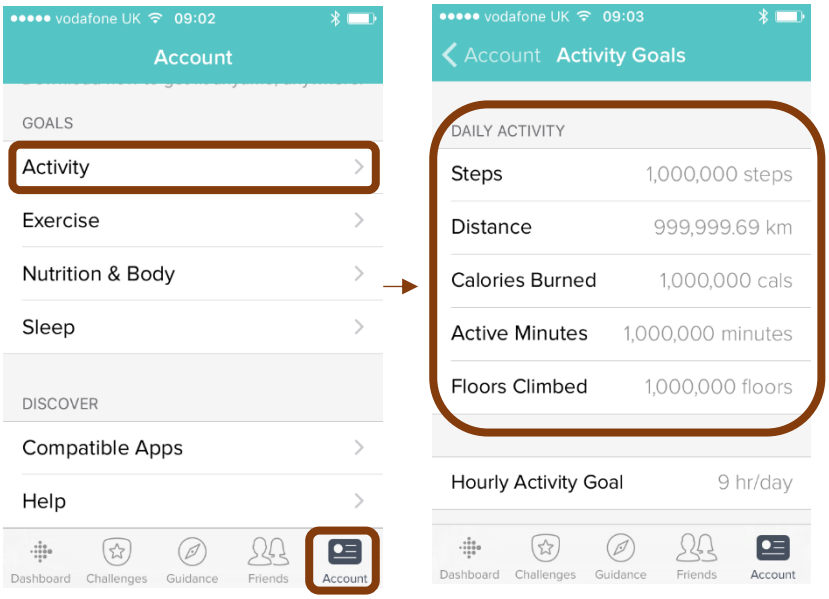
Dashboard:

On the dashboard, scroll down and press 'Edit'. Now de-select **all** metrics by pressing the grey buttons so they become pink. Now press 'Done'.

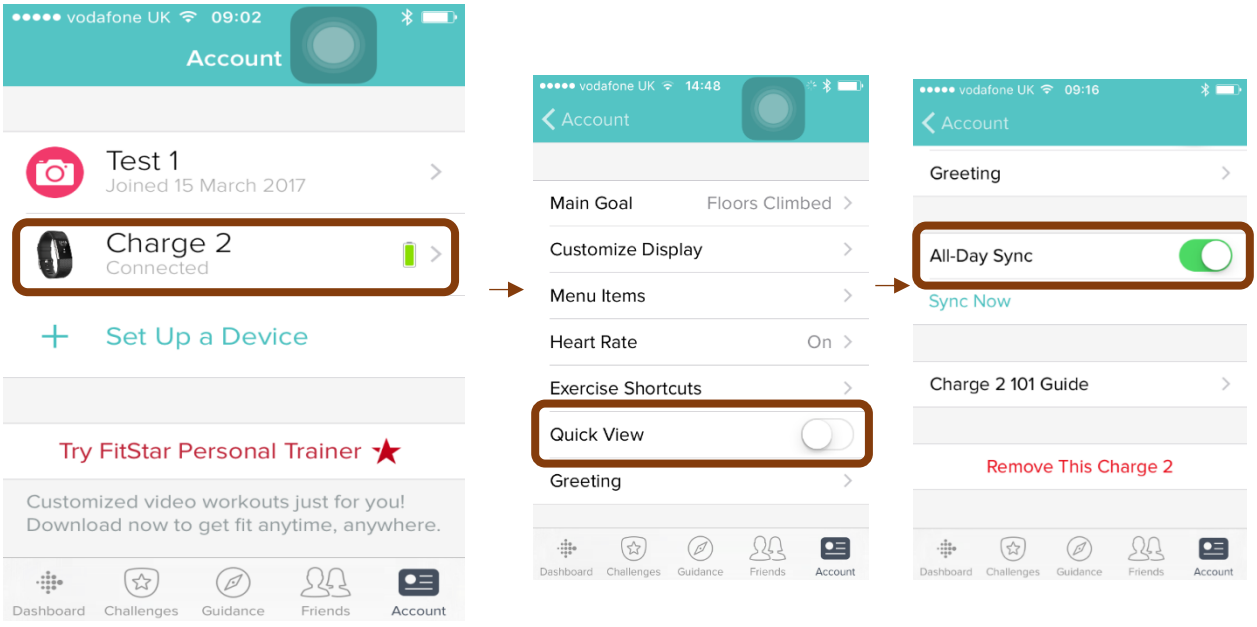


Account settings:

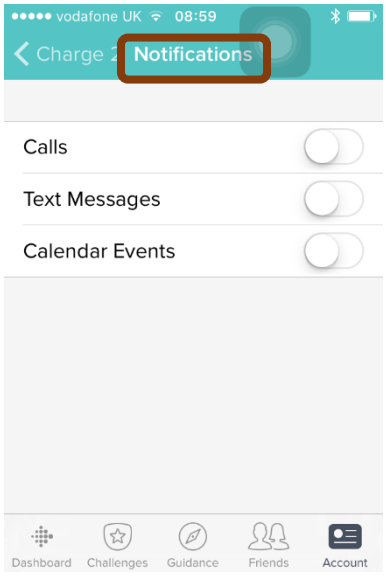
- Adjust the settings from default to the following numbers:



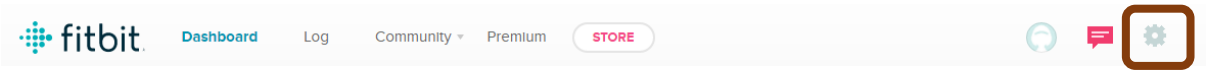
- Ensure that Quick View is turned **OFF** and All Day Sync is turned **ON**



- Ensure that notifications are switched **OFF**



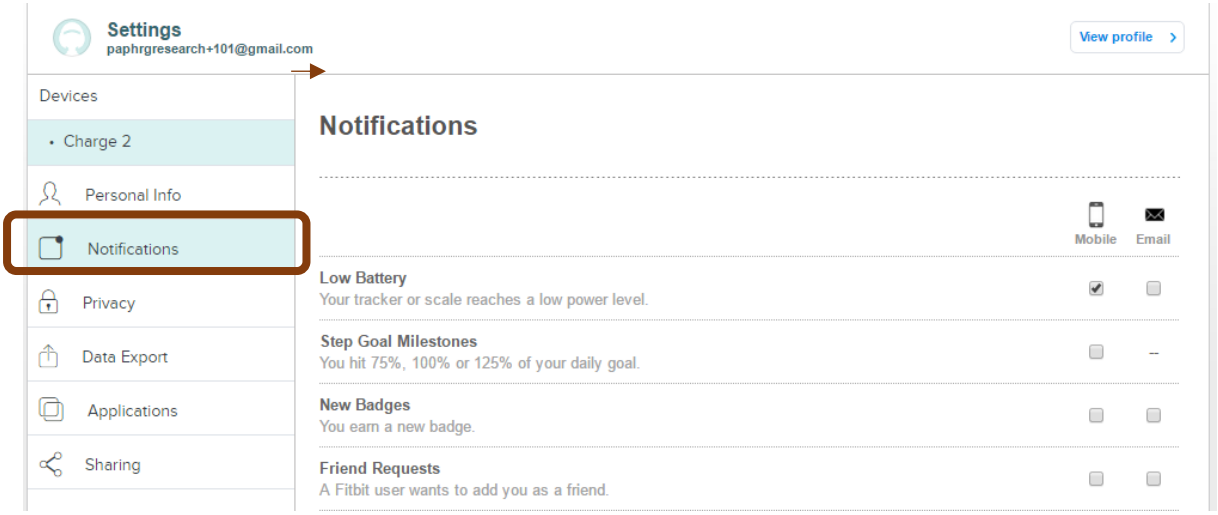
www.fitbit.com/login

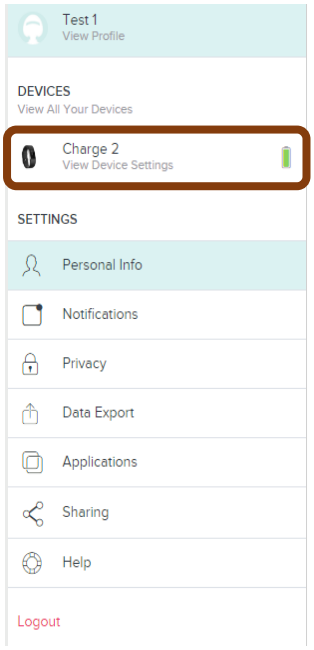


Settings

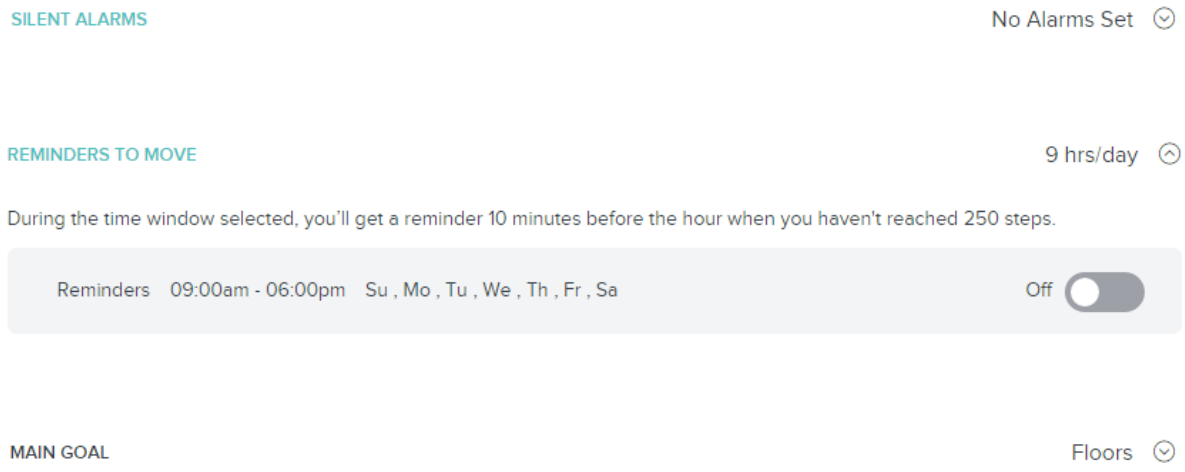
Notifications:

- **Untick** all boxes except 'Low Battery' under the Mobile column.
- Scroll down, **select** 'No emails' and click '**Save**'





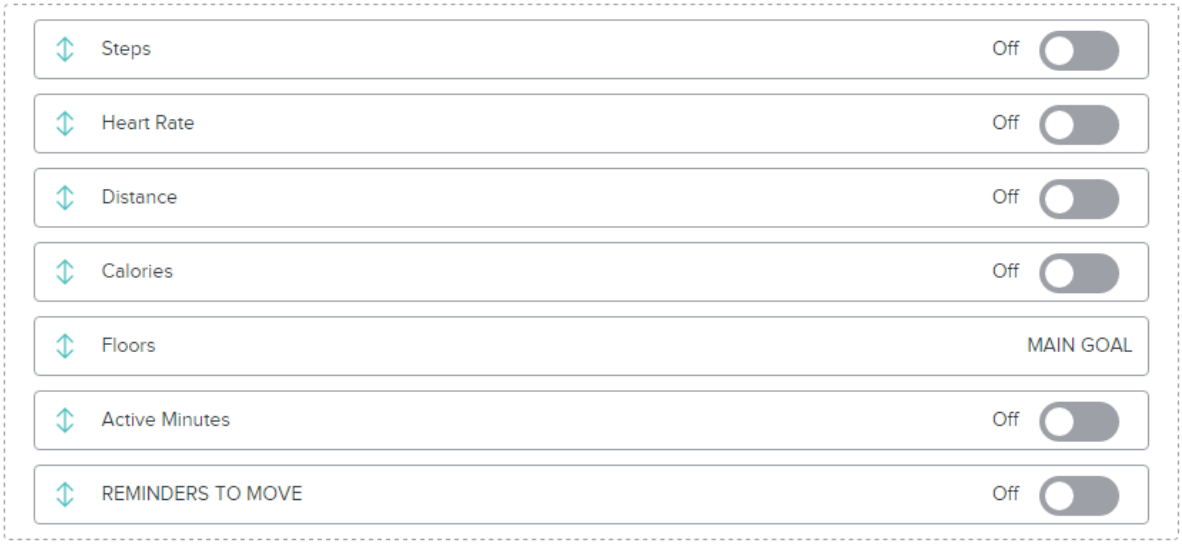
Charge 2: Ensure the device settings are set to the following:

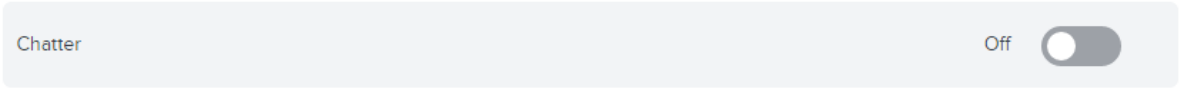


TAP DISPLAY

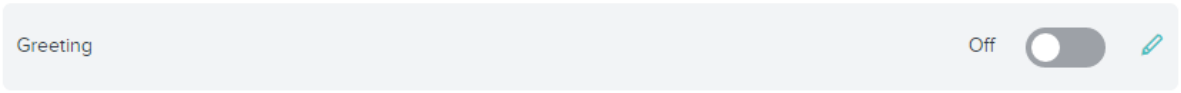
Edit

Customise what you see on your Charge 2 display by hiding and showing items. Drag items up or down to change the order in which they appear when advancing through stats.





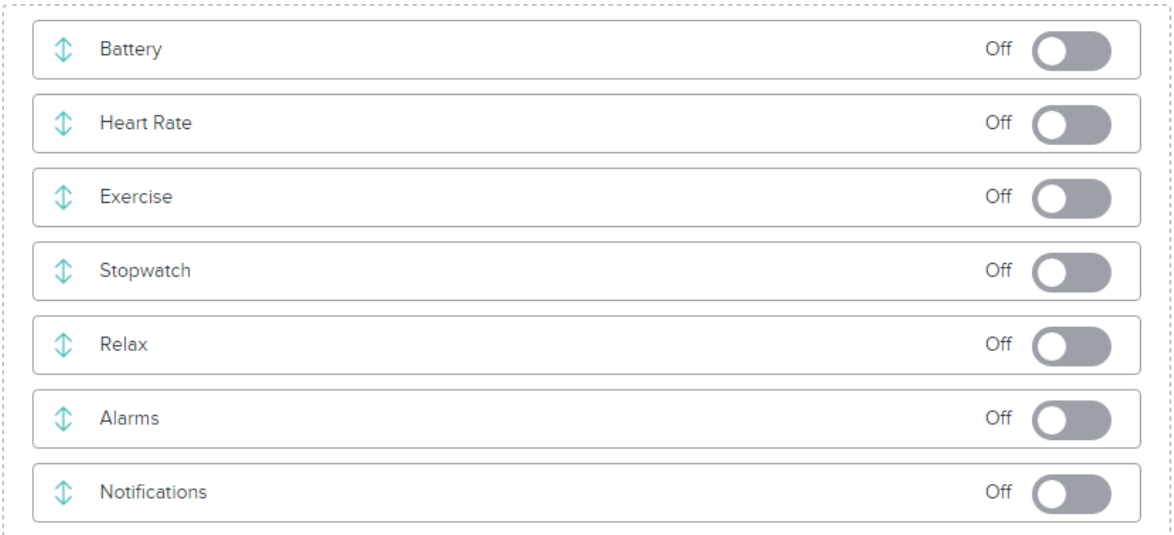
Turning on chatter lets us send fun messages to your Charge 2 throughout the day.

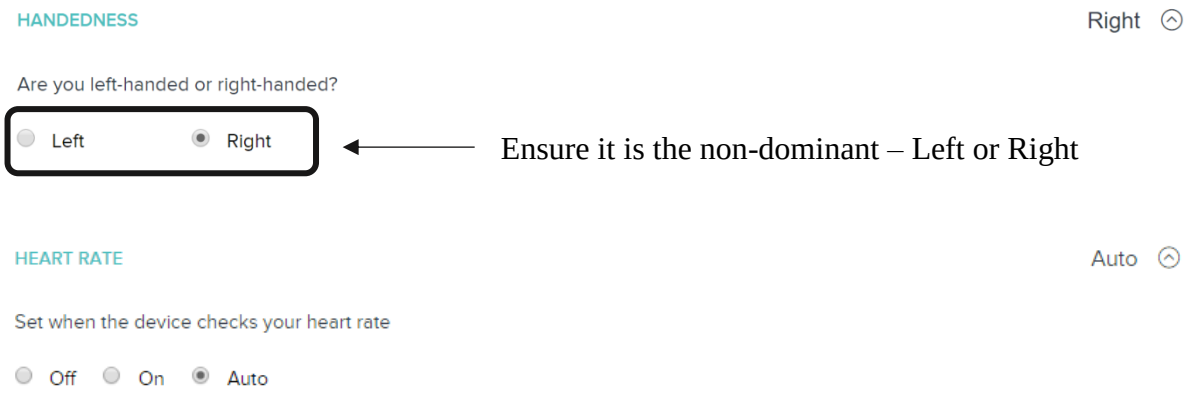


MENU ITEMS

Edit

Customise the menu items that you see on your Charge 2 display when pressing the button. Drag items up and down to change the order in which they appear.



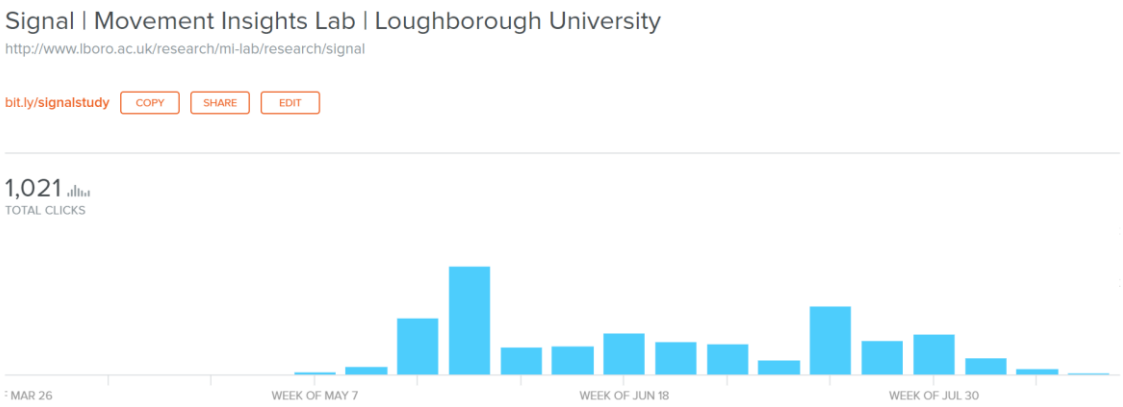

HANDEDNESS
Right
Are you left-handed or right-handed?
Left
Right
Ensure it is the non-dominant – Left or Right
HEART RATE
Auto
Set when the device checks your heart rate
Off
On
Auto

Appendix I

Sttudy Three: Additional information of the technologies used.

Bit.ly

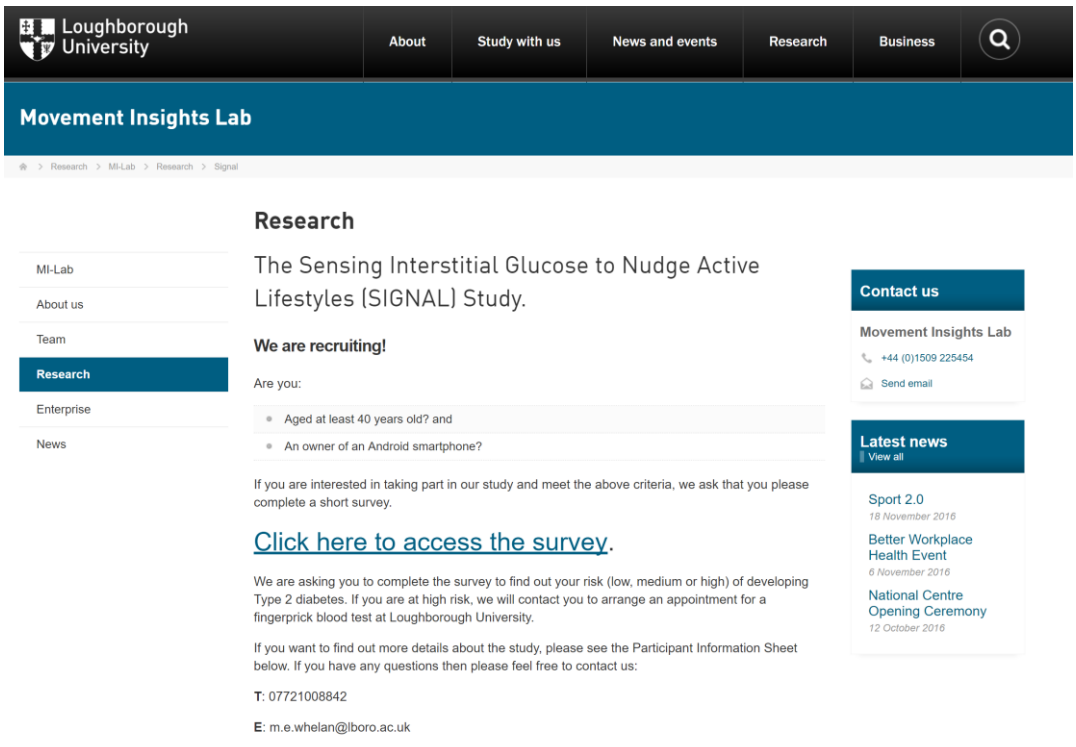
Interested individuals were directed to the SIGNAL Study website via http://www.bit.ly/signalstudy. Employing this website URL also allowed the research team to quantify the number 'clicks' or website visits that resulted.



An illustration of the bit.ly metrics

SIGNAL Study website

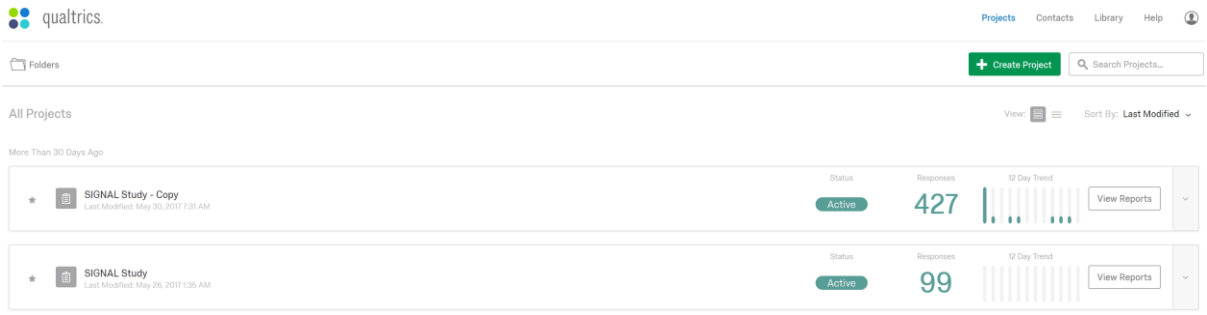
The SIGNAL Study website was constructed to advertise the study and offer the chance for interested individuals to access information about the study (including the participant information sheet). It also clarified that the research was being conducted at Loughborough University and offered direct access to the survey (via 'Click here to access the survey').



The SIGNAL Study website

Qualtrics survey

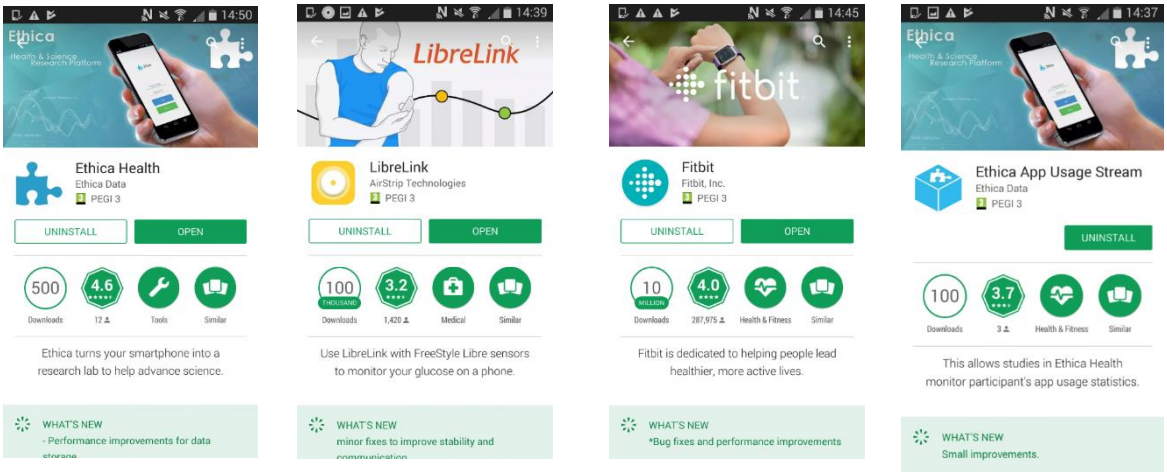
Upon clicking the link to access the survey, individuals were directed to complete a few questions to determine eligibility to take part. The survey, produced and published within Qualtrics (Qualtrics, Provo, UT) contained questions relating to demographics, body compositions and family history; mirroring questions used within the Diabetes UK Risk Assessment tool. To note, the question requesting waist circumference was amended to instead ask individuals to confirm their trouser waist size and fit. In combination, responses were used to calculate an approximate waist circumference measure. Using Qualtrics permitted access to individuals' survey responses to identify and contact potentially eligible individuals. There were two version of the survey: (1) 'SIGNAL Study' – identified high risk and (2) 'SIGNAL Study – Copy' – identified moderate-to-high risk. The first version was published live initially but after changing the inclusion criteria to include moderate-to-high risk, the second version was published live.



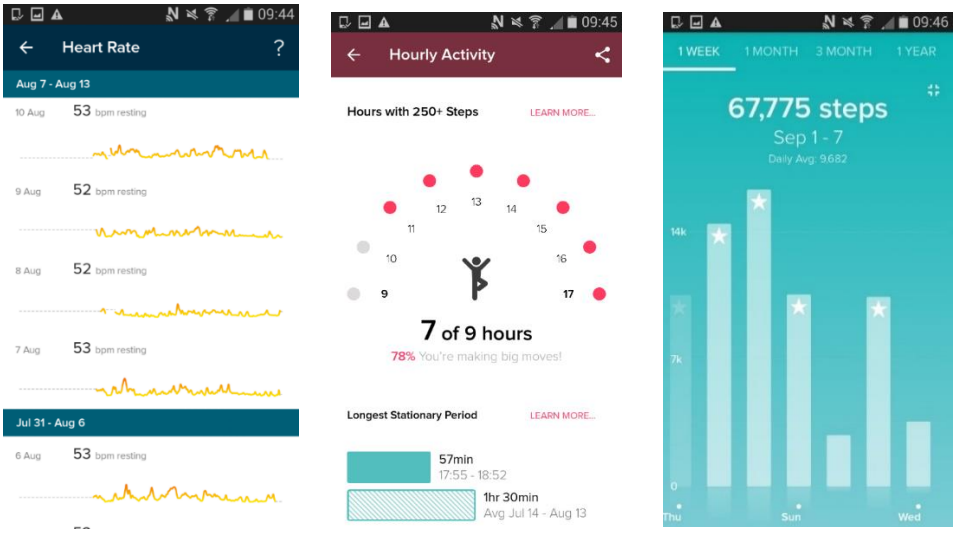
The Qualtrics dashboard

Participant smartphones

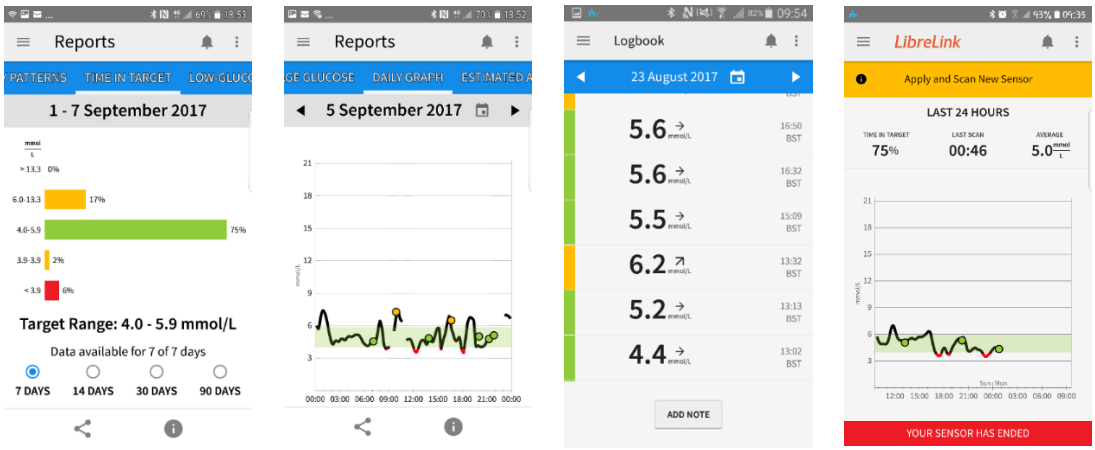
Participants were asked to install the following official applications.



The applications installed onto the smartphones



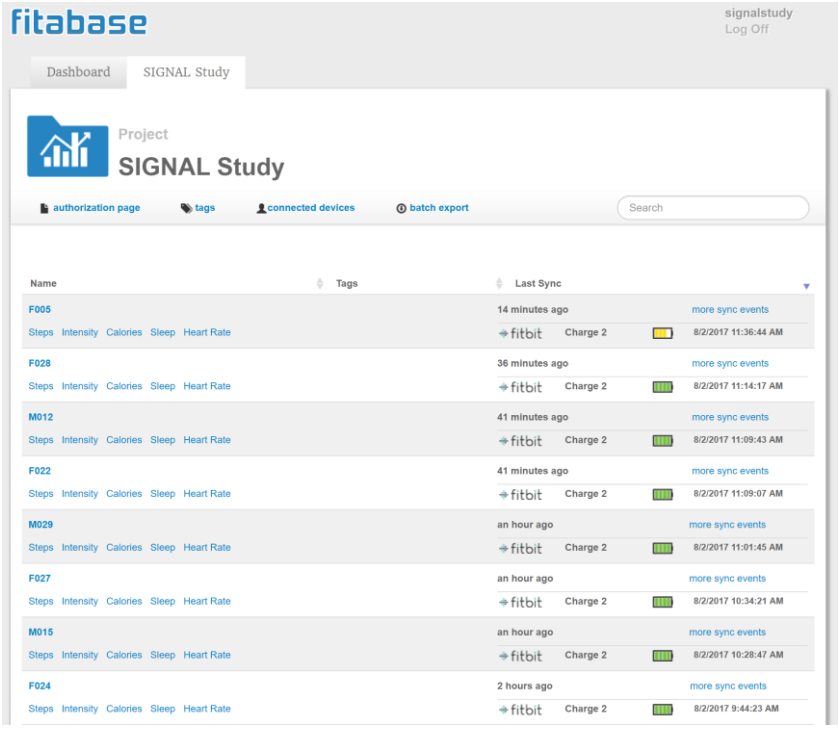
Screenshots of the Fitbit application



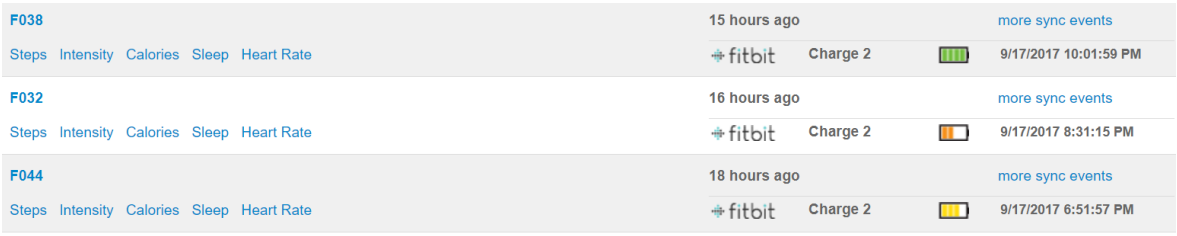
Screenshots of the LibreLink application

Fitabase

Fitabase is a fee-for-service online platform that allows access to minute-level data recorded by the Fitbit. Ordinarily, if data were to be exported from Fitbit directly, data would be recorded at a day level and would require only one sync every thirty days. Fitabase collects minute-level data by communicating with the official Fitbit application. The Fitabase dashboard (accessible via the research team) allows the opportunity to remotely monitor multiple Fitbit devices at one time. Fitabase records time-stamped logs of all syncs and battery status using data from the Fitbit application; allowing the researcher to identify compliance to syncing and charging.



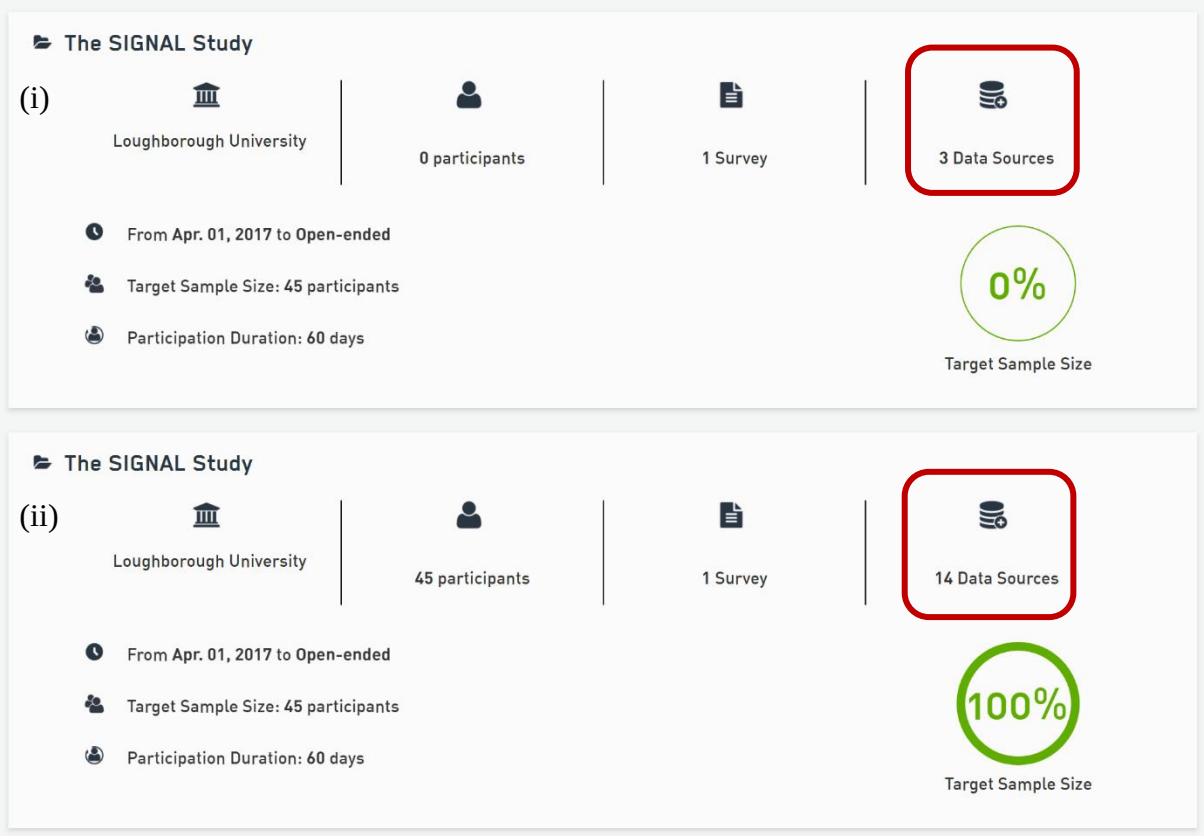
The Fitabase dashboard



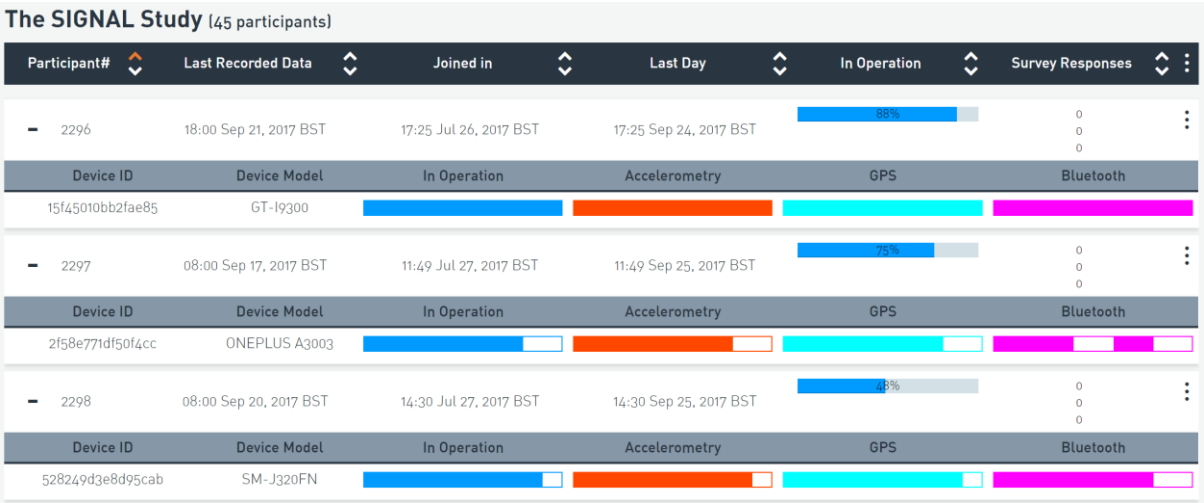
The Fitabase dashboard demonstrating battery status

Ethica Data

Ethica Data is a fee-for-service platform that records data directly from a participant's smartphone. Of note, Ethica Data allows the research team to remotely monitor enrolment into the study and data provision and monitor rate and regularity of incoming data. In the study, we employed fourteen data sources.



The (i) restricted (n=3) and (ii) full (n=14 data sources) coverage options



An overview of three participants' status to monitor data capture

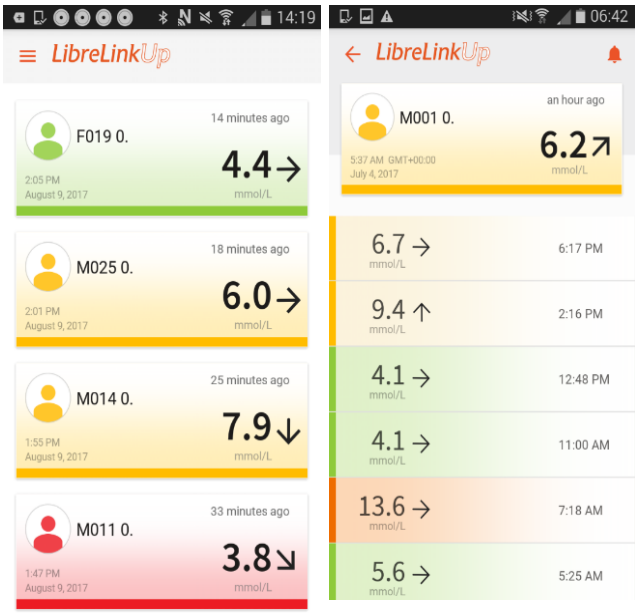
An overview of the data sources monitored

Data Source	Description
Location sensors	
GPS	Measures the precise location of the device using GPS sources.
Wi-Fi	Monitors Wi-Fi signals in the surrounding environment.
Motion sensors	
Accelerometer	Measures the acceleration forced applied to a device (Including force applied from gravitational pull).
Magnetic field	Measures the ambient geomagnetic field.
Gyroscope	Measures a device's rotation.
Linear acceleration	Measures the acceleration forced applied to a device (Excluding force applied from gravitational pull).
Gravity	Measures the force of gravity that is applied to a device.
Orientation	Measures the orientation of a device.
Pedometer	Count steps taken by the participant.
Contact network sensors	
Bluetooth	Monitors Bluetooth signals in the surrounding environment.
Digital footprint	
Screen state+	Records the time that the screen turns on or off.
Application usage+	Records how often an application is used.
Other	
Survey responses+	Records user responses to survey questions.
Battery status	Monitors the battery status of a device.

+Data sources included within the Restricted coverage of Ethica Data

LibreLinkUp

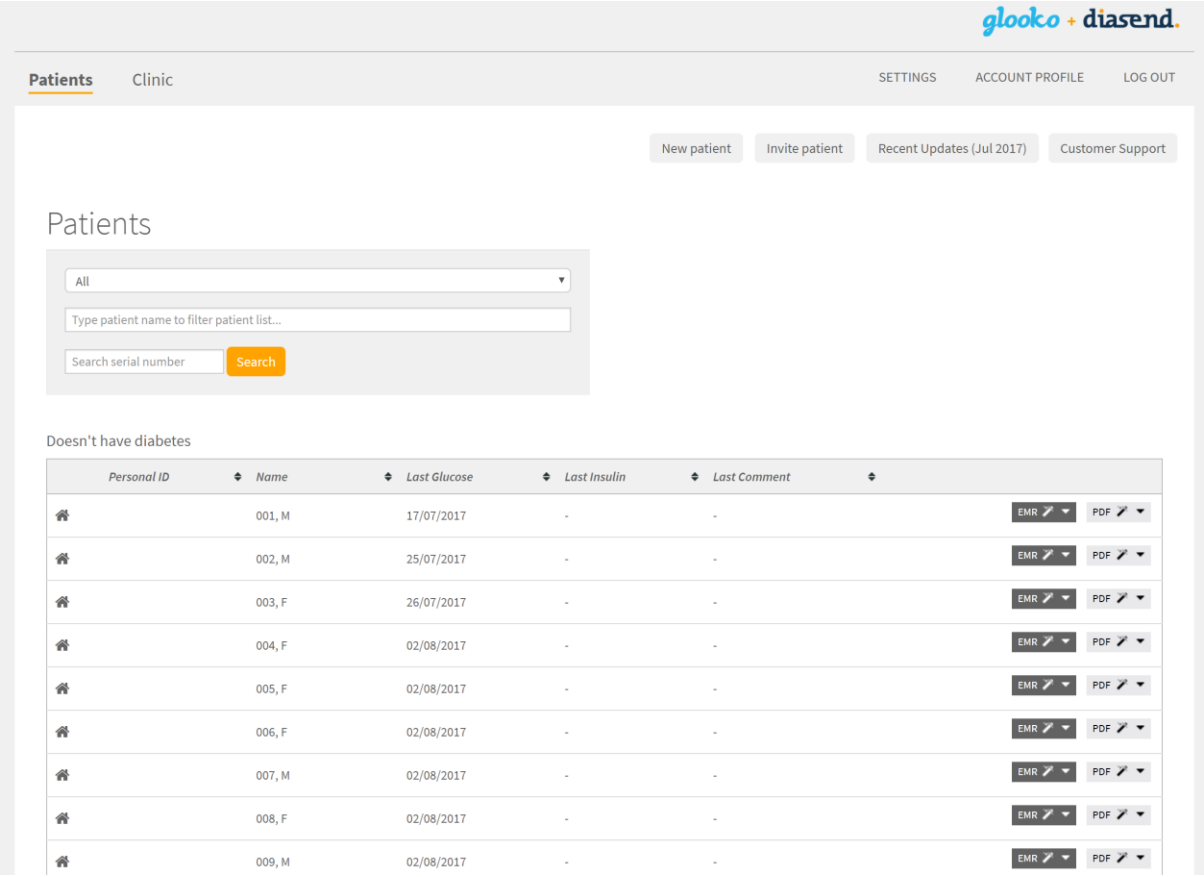
LibreLinkUp is a free smartphone application used as a software platform for the present study. Downloaded from the Google Play Store, LibreLinkUp collects time-stamped data reflecting each time a participant scans the Freestyle Libre sensor. This offers a real-time record for all participants and logs the data. Because the Freestyle Libre relies on users scanning at least once every eight hours to avoid data loss, determining whether participants have exceeded this can be identified using data collected from LibreLinkUp. This software also permits the research team to view multiple participants simultaneously by offering real-time data of participants scanning behaviour. In accessing this data, the research team are also able to monitor non-usage attrition. A maximum of 20 individuals can be monitored at one time so multiple email accounts of LibreLinkUp were employed for the study.



The LibreLinkUp application

Diasend Clinic

Diasend offers two different methods of setting up an account. Firstly, participants will have a personal account with Diasend (accessed only by the research team). This account permits the connection of a Fitbit and Freestyle Libre to subsequently retrieve data. To allow the research team to access each participant's data, these individual accounts are linked to a single Diasend Clinic account. Diasend Clinic is a fee-for-service platform that allows a researcher (normally a healthcare professional) to connect multiple individual accounts to retrieve data. The connection setup with the Freestyle Libre (via the LibreLink application) offers 15-minute epoch data over the study duration. This data will offer insight into wear time (transfer from one sensor to the next) and data loss (adherence to scanning).



The Diasend Clinic dashboard