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New technologies and innovative methods in data collection: scoping review

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Introduction

We live in an age where there are a proliferation of technologies in widespread use in daily life. With the rise in the availability of these new technologies and innovations, comes a rise in the opportunities to utilise them for research. An increasing number of people are using smartphones in daily life. The use of, and literature around, mobile web surveys is growing. However, as well as survey data collection done via a smartphone, there are other opportunities around innovative methods of data collection. In addition, there are large numbers of standalone devices that also enable measurement of various aspects of behaviour and the environment. These technologies offer us a plethora of opportunities to measure a wide variety of aspects of life that previously were not measurable, or that were captured via self-reports, which could be inaccurate for a number of reasons, such as social desirability bias or recall issues (examples of areas of study that have compared self-reports and objective measures and found self-reports to be unreliable include time use, Gershuny et al. 2017; physical activity, Prince et al. 2008; computer use, IJmker 2008, and; sedentary time, Healy 2011).

The literature provides us with two broad types of data collection when using new technologies and methods - active and passive. Active data is data requested from the respondent; the individual has to actively participate in provision of data. This can be through completing a questionnaire or other research instrument, or providing data through taking photographs, scanning barcodes or receipts and so on. Passive data collection, on the other hand, collects data about the respondent in a (usually) unobtrusive way. This can be through an app or widget on their electronic device which captures usage, a GPS tracker which sends information to the researcher about the respondent's location, or via wearables. Wearables have become particularly popular in research in recent years. A plethora of data can be collected by a multitude of different devices, without the respondent having to do anything other than ensure they are wearing the device.

When thinking about the use of new technologies for data collection, a number of issues must be considered. The scientific utility of data, including the research questions it will allow us to answer, should be paramount. Issues of measurement need to be explored, to ensure that we have a good understanding of what is being measured and how accurate and reliable these measures are. Representation is also important, as it may be that the people who participate in these types of data collections are not representative of the population of interest. There may be challenges around the ethics of different forms of data collection. Additionally, there are challenges around data access, processing, storage, archiving and analysis which need to be overcome.

Scope of this work

This report will explore the theme of innovative data collection from two angles. The first section will look at what major longitudinal studies have already done in terms of collecting data using new technologies and innovative methods. We will document the innovative data collection methods used on the cohort studies housed at the Centre for Longitudinal Studies, as well as other major longitudinal studies both in the UK and abroad. This information was collected directly from studies, as well as via searches in published and unpublished literature. Once we have discussed the work that has already been undertaken on longitudinal studies, we will broaden the search to look at technological innovation in other academic and market research settings. Finally, this section will conclude with a discussion of other possibilities for innovative data collection that have yet to be utilised in a research setting. There is currently very little published literature on the use of new technologies and innovations for data collection. As such, the information in this report has been collected from a wide variety of sources, including publicly available documentation, as well as from talks, seminars and conferences attended by the author and colleagues.

The second section of this report will explore the methodological challenges surrounding innovative data collection, including willingness of participants to take part in non-standard methods of data collection, take up rates and representation, measurement issues, ethics, practicalities for large-scale longitudinal studies, and cost.

On 25th June 2019, CLS held an event to further scope opportunities for the incorporation of new technologies for data collection within longitudinal studies. The learning from this has not yet been incorporated into this review.

Section 1: technological innovation and possibilities

Technological innovation in major longitudinal studies

Active

At the Centre for Longitudinal Studies (CLS), we have implemented a number of new technologies and innovations within our cohorts. Accelerometers have been used on the Millennium Cohort Study (MCS) and the 1970 British Cohort Study (BCS70) successfully, as well as a mixed mode time use diary on MCS at age 14.

At age 7, MCS cohort members were asked to wear waist-worn accelerometers. 14,043 children took part in the main interviewer data collection, and parents of 13,219 (94%) of them provided consent for their child to wear the accelerometer. 8939 accelerometers were returned with data, 64% of the Age 7 Survey participants (Griffiths et al. 2013). At age 14, MCS cohort members were asked to wear wrist-worn devices. Of the 10337 eligible cohort members who participated in the Age 14 Survey, 89% agreed to wear the accelerometer, and 48% returned a monitor with data (Ipsos MORI 2017).

BCS70 cohort members as part of the survey at age 46 were fitted with thigh-worn accelerometers, to capture information about physical activity and sedentary behaviour. Of the 7673 cohort members who participated in the biomeasure component of the survey, 6485 (85%) agreed to wear the accelerometer, and 5617 (73%) returned the device with data (Morgan and Taylor 2018).

MCS implemented a mixed-mode time use diary at age 14, collecting time use information via web, app and paper. Cohort members were asked to select between the app and web version of the diary, with paper reserved for those who could not or would not participate electronically. The app in particular was a departure from the traditional methods of collecting time use data, using a question-based approach instead of the more common grid format (Chatzitheochari et al., 2018). During the interviewer visit, 89% of eligible cohort members agreed to complete the diary, and 46% returned at least one day's worth of data. A more comprehensive description and analysis of the time use data is contained in the report by Emily Gilbert, Lisa Calderwood and Emla Fitzsimons, submitted in parallel to ESRC.

Understanding Society, on the Innovation Panel, have asked respondents to scan receipts using a specially developed app in order to collect spending data. The app allows entry by scanning, but also manual input. They have compared the app data with survey benchmarks (UK Living Costs and Food Survey), and found that the app performs well if both scanned and direct entry data are used. It does particularly well for clothes and footwear, and less well for food and groceries, and socialising and hobbies (assuming the benchmark is accurate). In terms of take-up, 13% of the invited sample used the app at least once, with some drop off in usage over time. Those who used the app were more likely to be women, younger participants, more educated respondents, and those people who actively managed their finances (Jäckle et al., 2019).

The Avon Longitudinal Study of Parents and Children (ALSPAC) has attempted to collect food consumption and purchase data through photography. They asked participants to take photos of their own and their child's food intake, plus asked them to complete two different online dietary diaries, in order to assess if consumption information could be captured more accurately using photos. They found that photographing food led to a much lower response rate and lower data quality when compared with the web-based food diaries, and as such online dietary questionnaires remained the preferred method to collect food consumption and purchase data over photographic methods (Johnson, 2017). The photographing of food to estimate consumption has also been piloted by the Dunedin cohort in New Zealand.

Passive

Growing Up in Scotland, as part of their "Studying Physical Activity in Children's Environments across Scotland" (SPACES) project, trialed the use of activity monitors and wearable GPS devices among a sub-sample of the cohort, when they were aged 10-11. The initial pilot used wrist-worn devices for both accelerometry and GPS, but the second phase moved to waist-worn for both. SPACES encountered issues with device loss through lack of return, as well as device issues such as battery life and data storage capacity. Overall, 40% of the sample agreed to participate in the data collection exercise and sent back data. In terms of who participated, when compared to the whole samples, the SPACES sample contained slightly fewer obese children, and more children living in more rural areas (McCrorie & Ellaway, 2017).

The Women's Health Study, in the US collected accelerometer data from 17,466 of its participants (for a response rate of 59%). They mailed accelerometers out to respondents, then asked them to post them back after data collection (Lee et al., 2018). The Survey of Health, Aging and Retirement in Europe (SHARE) have piloted the use of thigh-worn accelerometers to capture physical activity data from adults aged 50 and older in ten European countries. Around 50% of respondents who took part in the main SHARE interview agreed to wear an accelerometer. The piloting raised concerns about device return from field and subsequent re-use (Scherpenzeel et al., 2019).

Summary

These studies all highlight that response rates to components of data collection that use new technologies or innovative methods to collect the data tend to be lower than survey data collection. However, what is not yet fully known is the extent of the bias, if any, this introduces. More research is needed to understand the types of people that are willing to participate in innovative methods of data collection, and the ways they differ from non-respondents to these data collection requests.

Scoping the possibilities - technological innovation in academic and market research

Active

The UCL Institute for Behavioural Science has developed an app-based game called Sea Quest Hero which assesses spatial awareness, which among other things can provide an early indication of Alzheimer's) (Coutrot et al., 2018). The game has been used successfully on a large scale, but not previously combined with rich social, demographic and health data. The BCS70 team are currently exploring incorporating data collection via the Sea Quest Hero app into the Age 50 Survey, due to commence in 2020.

GfK, a global market research agency, have developed emotion recognition software, called Market Builder Voice, which records speech and measures intonation, pitch and volume to assess emotions, enabling a fuller picture of emotion to be created through what is said as well as how it is said. They have also developed a video version (EmoScan) which records the face to assess people's emotions (GfK Verein). These technologies are typically used in assessing the reaction to videos, such as adverts, in market research, but there is the possibility of using it to pilot questions during questionnaire development stages. They may also be useful tools for answering open-ended questions for those who struggle with writing.

TNS BRMB, a UK market research agency, were involved in a Change for Life evaluation where respondents reported certain food and drink purchases via an app, but were also asked to photograph them for validation purposes. 67% of those asked to take part agreed, and 80% of those continued participating throughout the three week project (Wrieden and Levy, 2016). The use of photographs alongside self-reported data potentially offers a way of assessing the quality of data entry.

TNS BMRB have also been involved in a location-triggered 'ringfencing' survey project. Sample members are asked to download an app, and then a survey is pushed to the app when they physically enter a particular geographical area. The purpose of this particular project was to understand how green spaces were experienced, but it could also be applied to a range of other locations and experiences. This study was presented to CLS by TNS BMRB in 2016.

Passive

Studies have used GPS to track participants' movement. The National Travel Survey (NTS) has traditionally asked respondents to complete a seven-day travel diary, but has piloted the use of GPS devices to capture travel instead of paper based methods. The NTS gave respondents GPS monitors to carry with them wherever they went for a week. They found that response rates for those carrying the GPS device were lower than the paper diary response rates – 52% versus 59%. The piloting also raised issues with device set-up in field, as well as problems with respondents returning the devices and their subsequent re-use in field (Humphrey, 2017). Eleveldt et al. (2018) did a very similar study, linking time-use data with GPS information from respondent's smartphones in order to assess the quality of the time-use data. They found that self-report data tends to match very well with the GPS data when linkage can be done successfully. However, linkage itself proved to be problematic. Linking self-report data with smartphone GPS data using the Android operating system was possible in 58% of cases, but for the iOS operating system this was much lower, at 3%. This demonstrates technical problems when assigning time to location, and is in part thought to be because it takes iOS devices in particular a certain amount of time to “switch on” GPS recording once movement has been detected.

The Dutch Mobile Mobility Panel project has asked respondents to download an app (MoveSmarter) onto their smartphone in order to use the phone’s inbuilt GPS, cellular signal and Wi-Fi signals to collect passive travel data for a three year period. The app worked across iOS and Android operating systems. A sample of members of the Longitudinal Internet Studies for the Social sciences (LISS) panel were asked if they would be happy to participate in such a project (the sample size of those initially approached is not reported). Those who did not own a smartphone would be provided with one. Of the 800 respondents who said they would, 655 (82%) actually started participation through installation of the app, and just over 550 (69%) continued with the panel for the whole duration (Geurs et al., 2015).

GfK, a global market research agency, have a number of technologies to monitor device usage, router usage and consumer spending for market research purposes. Their app and browser add-on LeoTrace can determine the frequency, duration and time-of-day use of various devices. In order to get around the issue of assessing who is using the device at the time, the add-on asks users to identify themselves at the start of each session (Knecht, 2012). This technology could be useful for longitudinal studies, as by looking at what respondents use the internet or their device for can tell us many things related to different spheres of life – for example, health (e.g. symptom checking), finance (online banking), social forums (how connected they are) – as well as seeing the frequency with which they are active on the device or computer. De Reuver and Bouwman (2015) conducted a similar study, whereby one group of participants were asked to download an app onto their phone to track device usage, and another group were asked to self-report the same information. They find that for some categories, self-reports underestimate device usage levels, resulting in misleading conclusions.

The Netquest panel, with panel members in 21 countries, have asked their participants to install an app on their devices to allow researchers to access device usage data. Some 13,500 people agreed to do so, a response rate of 30-50% across countries. Revilla and colleagues (2017) looked at the sample of panellists in Spain who agreed to install the usage app, and found that compared to the general population, 65-74 year olds and the “middle low/low” social class groups were underrepresented, and people living in large cities, those who were highly educated, the middle and upper social classes and 25- to 34-year-olds were overrepresented. They conclude that using the data from the app to make inferences to the population would be “dangerous”. They also found that a large proportion of the panellists do not install the app on all of their devices, against study protocol: for example, 96% of those who agreed to install the app had more than one device, but 57% only installed the app on one device. This means the full picture of panellists’ device use is often not being captured, leading to potential biases.

TNS BMRB worked with the Department for Transport on a research project aiming to assess the impact of a road safety campaign. The use of passive collection was well suited to the reflexive nature of driving. Data was passively collected by attaching a ‘black box’ device to the respondent’s car to assess whether they were more likely to slow down in particular areas (the objective of the campaign). Recent technological developments now mean that they can get respondents to download an app rather than attach a device to their cars, which increases coverage. This study was presented to CLS by TNS BMRB in 2016.

TNS BMRB also presented their “Life Loggers”; wearable cameras which can act as an alternative to ethnography and static photos. While they are currently being used for qualitative work, it can potentially be used for scaled up quantitative work as the images can be machine processed via code.

Ipsos MORI have developed technology, in the form of an app called MediaCell which can be installed on users' devices, which "listens" to background noise to determine radio, TV, cinema and other audio media consumption habits (Ipsos MORI).

There are a number of projects, including The Sensor Platform for Healthcare in a Residential Environment (SPHERE) project, the Intelligent Systems for Assessing Aging Changes (ISAAC) project and a study run by researchers at the Oregon Center for Aging and Technology (ORCATECH) that have deployed multiple sensors (including wearables, cameras, environmental sensors and appliance monitors) into the homes of their elderly study members to measure a proliferation of things, including daily activity, time away from the home, walking speed, gait, sleep patterns, computer use and medication adherence (Kaye et al. 2011; Lyons et al. 2015; Waznawski 2017). These types of studies offer the opportunity of capturing a detailed picture of the daily lives of participants without being overly burdensome.

The Labour Market and Social Security Panel (PASS) in Germany have conducted a feasibility study of using a smartphone app (the IAB-SMART app) to enhance data collection. This study collects data in multiple ways, from smartphone surveys, surveys triggered by events, and passive data collection through sensors (GPS, app use, websites visited, phone book entries, and phone signal strength). Sixteen percent of those invited to participate installed the app, and 75% of those were still using the app six months later. They have run into an issue in that the smartphone sensor data is only available for devices running the Android operating system (Haas et al., 2019).

Summary

There are a wide variety of new technologies and innovative methods of data collection available that could be utilised by longitudinal studies to collect data about a range of different topics, including device usage, consumption habits, and movements. However, much of this technology at present has only been used on small samples, and often by respondents who are already active members of opt-in online survey panels. This respondents may be more willing than the general population to participate in novel data collection exercises, demonstrated by their willingness to regularly participate in online panel surveys.

These small-scale studies have also uncovered issues surrounding the technology, such as operating system-specific availability and limitations, which would need to be resolved before these technologies are deployed on large-scale studies.

Are there other possibilities?

As technologies are developed and improved upon, new opportunities become available for research. Recently, Apple introduced a new feature in their OS which automatically records total screen time, and breaks it down by different categories (social media, productivity, entertainment etc.) and app-by-app. This information could be used as an alternative (or complementary measure) to self-reported screen time.

There are devices on the market that can measure blood-alcohol level on a real-time basis, using transdermal alcohol concentrations. The WrisTAS and SCRAM devices, wrist worn and ankle worn respectively, have been field-tested in small scale studies. However, the reliability of these devices has been questioned, especially for measuring episodes of low-level alcohol consumption (Greenfield et al., 2014). BACtrack Skyn is a wrist-worn device new to the market which gives an estimate of blood-alcohol level in real time. There are a number of other devices to do this in prototype, including Quantac Tally.

Google have developed the Verily Study Watch, which is a wrist-worn device that contains a variety of sensors to capture different information (ECG, heart rate, electrodermal activity, movement). It is Wifi-connected, and sends back information constantly. However, there are issues around privacy and data protection. Researchers intending to use the device have to partner with Google, and Google would have access to the data.

SurveyMotion is a Javascript-based tool which can measure motion/acceleration. It has been field-tested to establish whether it can be used to detect what someone is doing when they complete a survey on their smartphone. The tool can accurately distinguish between moving and non-moving conditions, which could perhaps be used as a proxy for concentration during survey completion (Kern et al., 2019). The tool has also been used in a pilot to establish whether it's possible to collect physical measurement/function data as self-completion. Respondents were asked to hold their phone in front of them while doing squats, and tap the screen for every squat completed. SurveyMotion ran in the background to detect whether there was any movement. Sixty one percent agreed to do the task, 43% did the task for the full minute, 29% partially complied, and 29% did no squats (Eleveldt et al. 2019).

Progress is being made is taking data from research accelerometers and consumer wearables (such as Fitbits) to understand behaviours other than physical activity. Stopwatch uses accelerometer and gyroscope data from a consumer wearable device to detect the signature hand movements of cigarette smoking. It uses machine learning techniques to transform raw motion data into motion features, and in turn into individual drags and instances of smoking (Stone, 2017). Sleep is another research area that is benefiting from development in accelerometer data algorithm development, with researchers increasingly able to understand more about sleep through this data (Lauderdale et al. 2014).

The proliferation of sensors now built into modern smartphones also provides a wealth of opportunities in terms of data collection. Data collected from GPS, Bluetooth, proximity sensors, Near Field Communication (NFC), and about cellular and Wi-Fi connectivity can provide information on some aspects of device usage, as well as track the device geographically. Sensors measuring air humidity, temperature and air pressure can tell us about the respondent's surroundings. Inbuilt gyroscopes, pedometers and accelerometers can provide insights into physical activity. Additional sensors, including cameras, compasses, fingerprint sensors, light sensors and the microphone offer additional research opportunities.

Along with these vast opportunities inevitably come costs and considerations that need to be overcome before we can successfully implement data collection on large-scale studies.

Section 2: methodological challenges

This section will discuss some of the major methodological challenges faced when implementing new technologies and innovative data collection methods in large-scale longitudinal studies, including wiliness of participants to take part, take up rates and biases, measurement issues, ethical issues, practicalities and cost.

Willingness of participants

One of the major challenges of using innovative methods of data collection is persuading respondents to agree to take part, and then to comply with the study protocols. There are a few studies that have explored willingness to perform different data collection tasks, and the factors associated with willingness.

Revilla et al. (2018) asked respondents of an online panel survey to report whether they would be willing to take part in a variety of different tasks. They found that respondents were more willing to do tasks where they had some degree of control over what data was handed over to researchers (such as tasks that involved taking photos), and less willing for more passive or tracking-type tasks (such as installing a tracking app on their smartphone). The authors find evidence that the lower levels of willingness to complete tracking-type tasks was probably down to concerns around privacy.

When looking at respondent characteristics which may influence willingness to participate in innovative data collection tasks, Keusch et al. (2019) find that respondents who use their smartphones for many different activities are more likely to say they will participate in a passive smartphone data collection activity compared with those who have less familiarity with different features of smartphones. Very similar results were found by Wenz et al. (2019), who also find that respondents who are more concerned with data security and privacy issues are less likely to report being willing to participate in a mobile data collection task.

More research needs to be done to assess the factors associated with stated willingness and subsequent participation in different innovative data collection tasks.

Take up and representation

A major issue with the deployment of new technologies for data collection is take up and representation. Take up rates tend to be lower than traditional survey data collection response rates (for example, see Howie and Straker, 2016, for a review of missingness in child accelerometer studies), and often those who agree to participate in new forms of measurement do not necessarily represent the sample as a whole.

Examining data from Whitehall II, Hassani and colleagues (2014) found that those individuals who had refused to participate in accelerometer data collection tended to be female, those reporting less physical activity in the self-report question and those reporting worse health overall. The refusers also tended to have lower cognitive ability (measured at time of interview), and a slower walking speed. Also looking at accelerometer data, Roth and Mindell (2013) found that participants of the Health Survey for England who complied with a request to wear an accelerometer for a sufficient amount of time were different from those who agreed to wear an accelerometer but then didn't wear it for enough time, but not significantly different from those who refused to wear the monitor in the first place.

We also need to be aware of who has the technology required to participate in the first place. Much innovative data collection now involves smartphones, be that smartphone surveys or collection of data from smartphone sensors. Ofcom reported that in 2018, 78% of UK adults reported being smartphone users (Ofcom, 2018). This means that at that time, 22% of UK adults didn't use a smartphone, and this group of people are likely to differ from smartphone users in important ways. Additionally, some data can only be collected from smartphones which run certain operating systems, such as Android but not Apple. It may be that Android and Apple users differ.

There may also be differences in those who comply with the request for innovative data collection initially, and then after some time stop participating, and those who continue to comply for a longer period of time. More research is needed to understand the reasons that some people aren't willing to participate in innovative data collection tasks, why some people initially comply and then drop out, and key differences between those who comply/participate and those who don't.

Measurement

New technologies offer us new measurement opportunities. We may be able to capture information that previously was difficult to measure with self-reports, and are also able to measure things in real-time, and at much finer granularity. However, one of the key things to understand when considering the use of new technologies for data collection is exactly what the device or method is measuring – and whether the measurement can be considered a direct replacement for self-reported measures, or should be treated as complimentary.

It has already been established that self-reported data in a number of spheres can often be inaccurate or unreliable (IJmker 2008; Prince et al. 2008; Healy 2011; Gershuny et al. 2017). However, few studies have explicitly compared data collected using new technologies or methods with self-reported data. Additionally, there has been little examination of the data quality, validity and reliability of measures captured through new technologies or methods in a standalone way.

One exception is in the field of accelerometry, where a number of studies have been carried out to assess the reliability of consumer-based physical activity monitors. Studies find varying reliability across devices, particularly in "free living" situations, and accuracy is also dependent on the anatomical placement of the device and walking speed (Lee et al. 2014; Evenson et al. 2015; Bock et al. 2017; Chow et al. 2017).

Validation studies are also being done in the field of transdermal alcohol measurement to understand the relationship between transdermal measures of alcohol and peak breath alcohol concentrations – i.e. wrist worn devices versus more traditional breathalysers. Findings suggest that the relationship between the two measures differs for men and women, and recommends more work on this topic in non-lab settings (Hill-Kapturczak et al. 2015).

A major issue to consider in relation to measurement is feedback. Some devices which could be used to capture data for research purposes provide the user with feedback about the information collected – for example, an activity tracker may show the user how many steps they have done. There is concern that this feedback can impact the behavior of a respondent. More research is needed to understand how much of an issue this is.

Ethics

The ethical issues surrounding the use of new technologies for data collection are complex.

The risk of disclosure is an issue which must be addressed when designing and implementing an innovative data collection exercise. It may not always be clear where data is stored (on the device itself versus on a 'cloud'), or who has access to the data (just the researcher, the user, or maybe the manufacturer of the technology?). The same questions can be asked of data ownership. Researchers also need to consider whether data collected via innovative methods could be disclosive, and put into place steps to mitigate that risk.

Practicalities

The use of innovative methods and devices to capture data provides its own set of practical problems. Many devices rely on batteries to work, leading to issues around ensuring sufficient battery life to capture the data required in field. In the context of large-scale longitudinal surveys, where often devices are placed by multiple fieldworkers as opposed to being office-administered, this can be challenging. In a similar vein, the storage capacity of a device can present similar problems.

Technical failure can also cause problems in this sphere, creating missing data.

There is also the issue of matching data from devices with the correct respondent, a challenge when thousands of participants are involved and devices may be used by more than one respondent across a fieldwork period. It takes careful planning and thorough data reconciliation methods to ensure this is done correctly in the case of large scale longitudinal surveys.

The data provided by new technologies and other innovative methods of data collection also provide challenges in terms of storage, processing, archiving and analysis. The data files are often very large, causing problems with storage capacity available. For example, the accelerometer data files for the MCS age 14 data collection were up to 750MB per respondent, meaning nearly 4TB of disk space was needed to store these files alone (Gilbert et al. 2017). The same is true for archiving the data. In terms of processing the data, often different skills and expertise are needed to transform the data into a format useable by researchers. The same issue is present in terms of analysis; the skills needed to analyse traditional survey data are often markedly different from those needed to appropriately explore data from devices such as GPS trackers and activity monitors, for example.

Cost

Whilst wearables are becoming cheaper as the market develops and expands, the expense of deploying such devices on large-scale longitudinal studies is still large. For example, the accelerometer used for the Age 14 Survey of the Millennium Cohort Study cost £144 per unit. Scaling that up to cover a cohort of over 10,000 is obviously very costly, even when devices are “recycled” – i.e. used by more than one respondent – in field. For the Age 14 Survey, around 4,000 devices were purchased, pushing the cost of the technology alone to over half a million pounds.

One way to reduce the cost of innovative data collection is to make use of data from devices that are already owned by respondents. However, this brings with it a range of issues, from bias introduced through differences between device owners and non-owners and take up rates more generally, through to technical difficulties with accessing this data.

Summary

There are a large number of opportunities to enhance traditional survey data collected by large-scale longitudinal studies by collecting data through innovative techniques. The possibilities for more finely granulated and real-time measurement, without some of the draw-back of self-reports, such as recall issues or social desirability bias, are attractive for research. However, with these opportunities come a number of costs and challenges.

More research is needed to understand biases introduced through the use of new technologies and innovative data collection methods. We need more work to identify exactly what is being measured by different devices, and whether it can be considered a replacement for asking survey questions about certain behaviours, or whether these are complimentary measures.

Understanding who participates and who does not in data collected using new technologies and innovative methods, and how these people differ, will be crucial to ensuring high-quality research can be produced using new methods and devices.

Given the rapidly changing nature of this sphere, the ethics, practicalities and costs associated with innovative data collection are ever-changing. Keeping up with developments will be paramount in ensuring large-scale longitudinal studies can utilise the opportunities offered by new technologies and innovative data collection methods to provide the research community with relevant, high-quality, valuable data.

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