Wellbeing Measurement
A Guide to **Quantitative** Data Collection

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CONTENTS

About this resource

Context

Over the last four years **Happy City** has accumulated knowledge and experience of wellbeing data collection and analysis through the design, development and piloting of pioneering wellbeing measurement tools the **Happiness Pulse, Happy City Index** and **WellWorth policy toolkit**.

Happy City has specifically focused on urban wellbeing in the development of a wellbeing measurement tool that could contribute to a city-wide model of progress: The Happy City Index measures key wellbeing factors that would be missed if the traditional measures of economic growth such as GDP, were used to estimate the benefit of interventions to society. The tool brings together a number of existing wellbeing measures to derive a holistic assessment of wellbeing that captures how people are feeling and functioning in their everyday lives.

The survey instrument – the "Happiness Pulse" – was developed in partnership with the New Economics Foundation (NEF) with the dual aim of collecting citywide wellbeing data and engaging individuals and communities in the measurement and promotion of their own wellbeing. We explore details of the 2016 Happiness Pulse pilot in this guide.

The WellWorth policy toolkit, developed in partnership with the University of Exeter, is a digital tool that provides valuable information on the individual and societal benefits of wellbeing interventions. This innovative translation tool uses wellbeing data to inform local policy; a promising new approach to policy decision-making.

This guide shares our learning to help you, whether you're using Happy City products and services or not, to make better decisions about collecting wellbeing data and design more effective and reliable ways of making it reality.

The guide covers traditional ways of collecting quantitative wellbeing data such as the different types of surveys and questionnaires. We also cover some of the more novel, often digital and other technology-based, options for gathering wellbeing data, as these methods are rapidly gaining traction.

Who can use it?

- Anyone wanting to collect wellbeing data within their organisation, small group or community
- Those wanting to get a snapshot of how individuals are doing right now within your group or organisation

- Those wanting to collect wellbeing data to evaluate a specific wellbeing intervention

This guide will help you to:

- Understand the variety of ways you can collect quantitative wellbeing data
- The advantages and limitations of different types of methodology
- Assess the most appropriate form of data collection based on what sort of data you want to get
- Get some ideas about how you might use this data to inform decision making

1.0 Wellbeing and researching it

1.1 What do we mean by wellbeing?

To appreciate what wellbeing means, we need to first understand the concept of **subjective experience:** the idea that one person's experiences will be entirely from their own, single point of view. There can be no external frame of reference to compare two subjective experiences. For example, if one person reports they feel 55% sad and another says they also feel 55% sad, although both individuals offer us the same percentage we have no way of knowing whether each individual's 'sad' experience is exactly the same. The *subjective experience* of each individual is unknowable as we are unable to experience something exactly as someone else might.

The concept of wellbeing has been notoriously difficult to define for both individuals and researchers. Valid and reliable assessments of wellbeing rely on being clear about the specific 'thing' being measured and how the resulting data should be interpreted. Ultimately, it refers to how people are feeling and functioning in their everyday lives. 'Feeling' refers to emotions such as anxiety or happiness, and 'functioning' with things like feelings of connectedness to others or sense of competence. Generally people can evaluate their wellbeing using life satisfaction scales or comparison to 'the best possible life' in the form of numerical or statistical data.

Many describe *dimensions* of wellbeing such as positive affect, low negative affect, sense of purpose and overall satisfaction with life, but a universal definition has not yet been established.

Today it is generally agreed that **wellbeing is**:

- *Multidimensional:* incorporating all aspects of our lives essential for happiness e.g. social, physical, psychological
- *A positive concept:* considering both an absence of negative aspects of life and the presence of things needed to live a good life, e.g. healthy relationships, self esteem.

Importantly, **subjective wellbeing** is the more scientific term for **personal wellbeing**, which people often feel is a clearer, more accessible term (ONS, 2013).

Wellbeing and **happiness** are often used interchangeably. Although happiness is a central component of wellbeing, it refers to the emotional element of the experience: something we might feel moment-to-moment.The *feeling* of happiness, in contrast to having all the things that should theoretically make someone happy (e.g. money, good health) is the difference between **objective wellbeing** and **subjective wellbeing**. Objective being something that can (arguably) be measured externally, and subjective being something that only the individual can report on. **Resilience** is often linked with wellbeing and refers to capacity to recover from difficulty. Whereas wellbeing varies in different contexts and between individuals, resilience is dynamic and can be 'built' to increase ability to cope with future stressful situations.

1.2 Why measure wellbeing?

- *A sustainable measure of progress*: Wellbeing is at the heart of what many organisations do and wellbeing interventions can take many forms. Being able to demonstrate the value of what you do with valid and reliable data can be instrumental in securing continued support for your work.

- *People powered decision making:* Understanding how people are feeling and functioning in your organisation provides meaningful data to inform decision making.

- *Intrinsic value to individuals and society*: People readily identify with the kind of happiness and wellbeing that ties humanity together across cultures and time. Wellbeing depends on universal things like, the quality of our relationships, the health of the environment and strong communities filled with a sense of belonging and purpose. Wellbeing promotes balanced, resilient, supportive, far-sighted and caring behaviour.

- *Wellbeing is the focus of a number of policies and projects at all levels* – from international level actions including the Millennium Ecosystem Assessment which linked changes in environments to changes in human well-being to actions at a local level, with wellbeing facilitators being used by local doctors in an attempt to reduce burdens on health services.

1.3 The challenges of collecting wellbeing data

Many organisations intuitively know that wellbeing is important or that what they do in their organisation might be good for wellbeing. Collecting wellbeing data can be tricky and for many organisations struggling with time and resources, wellbeing data-collection can often feel like a luxury.

Why is wellbeing not on the agenda?

- ➔ **Ambiguous definition-** As described above, wellbeing can be hard to define. This makes measuring it difficult and wellbeing data often gets a bad reputation for being 'wooly' and lacking punch.

- ➔ **Relatively intuitive findings-** Many people feel they have an intuitive grasp of what wellbeing is and what determines it. Wellbeing measurement tools in comparison are often quite crude, providing limited information beyond what we would intuitively recognise to be true. For example, a typical finding might be "*The wellbeing scores of unemployed people are on average lower than that of employed people*". A lot of people might predict this kind of result, have an understanding of why this is and the many factors and nuances behind it. This can sometimes make measuring wellbeing feel slightly redundant.

- ➔ **Rigour versus pragmatism**- Policy-makers, funding bodies and academics generally prioritise how 'rigorously' wellbeing data has been collected and analysed. Quality is crucial to conducting ethical social research as findings have implications both within the academic world and wider society. When making decisions based on data, people need to feel confident about the quality of evidence they are relying on. Understandably, this can put people off collecting wellbeing data if they don't feel it will be taken seriously. For frontline organisations with less time and resources to conduct highly controlled scientific research, there needs to be a balance between rigour and pragmatism. Collecting data that is 'good enough' may be better than not collecting data at all. It is possible to collect good quality wellbeing data even with limited time and budgets.

- ➔ **Cost-** Some methods of wellbeing data collection are more costly than others in terms of time, people and money. This guide can help you choose the most feasible data collection methods for the scale of your project and the research questions you want to answer.

- **Resources and know-how-** Wellbeing is still a relatively new concept for many people, and there may be misconceptions about what it actually takes to collect and analyse wellbeing data. As well as tips covered in this guide, there is a huge range of open-source support for conducting social research available on the internet (See **list of useful links**).

- **Engagement-** Wellbeing measurement has traditionally been thought of as an extractive process- it's a bit tiring and sometimes painfully slow! With increasingly available technology we are learning more about how we can engage people with their own wellbeing measurement as something of value whilst motivating people to collect good quality data. Throughout this guide and our accompanying qualitative data-collection guide (**here**), we discuss how different methods of data-collection present opportunities to engage people with the wellbeing measurement process.

2.0 Getting started: things to consider

2.1 Validity and Reliability

Data is information, and it is only meaningful to the extent that it is both valid and reliable. If you want to collect wellbeing data you need to be thinking about the validity and reliability of the information you are collecting **before** you start.

Once you have analysed your data, the extent to which you can conclude anything meaningful from your findings will depend on the validity and reliability of: your wellbeing measures, the sample you have used and your method of data collection. Of course you may not be able to tick all the boxes, and most research will be a compromise between scientific rigour and pragmatism depending on the organisation carrying it out. However, if you understand the validity and reliability limitations of the data you have, you can make conclusions that accurately reflect your data and communicate your findings honestly.

Reliability

- The degree to which a measurement tool provides consistent and reliable results- the 'repeatability' factor
- Reliability may be across time or across measurement tools that measure the same thing (like wellbeing)
- If more than one person is observing the same behaviour, all members should agree on what is being recorded to ensure reliable results
- If two alternate measures claim to measure the same thing- e.g. wellbeing, you would assume similar results for the same person taking two different tests
- To be reliable, results at two timepoints from the same measure should be very similar if not the same
- Importantly, measuring reliability depends on the thing you are trying to measure. For example, intelligence is considered to be a relatively stable trait across time, so if the same person took the same test several months apart you would expect the result to be about the same. However, self-esteem or wellbeing can fluctuate much more often. Therefore, you might only expect the same result if given twice to the same person in a short time period.

Validity

- Refers to how well your research measures what it *intends* to measure

- Is about the credibility and believability of your findings: are the findings genuine?

- **Internal validity**: the instruments or procedures of a study measure what they intended to measure. Does your wellbeing survey ask questions that are relevant to wellbeing? For example, you might not ask questions about how many bars of chocolate people eat during the week to determine their wellbeing. Although for some, chocolate may offer some positive feelings, it has not been scientifically proven as a key factor essential for wellbeing unlike 'sense of purpose' or 'connectedness to others'. The links between chocolate consumption and wellbeing is an example of the complex relationship wellbeing can have with lots of variables. A relationship (or correlation) between two things does not imply cause and effect. In fact, the brand of chocolate bar, overall diet, activity levels and enjoyment of chocolate could be the key factors affecting wellbeing. In the long-term, eating large amounts of brightly coloured sugar-coated chocolates could have negative health consequences that reduce wellbeing.

- **External validity-** how well the results can be generalised beyond the study to other people and other situations. For example, if an organisation asked their staff members to provide their personal scores from a wellbeing survey with questions relating to 'happiness in the workplace' the results would **not** have high external validity. This is because their results are probably going to be influenced by the fact that they have to show the boss their scores! If the situation was different, and their scores were anonymous they might complete the survey more honestly.
    - **Population Validity**- (a type of external validity) The extent to which the findings can be extrapolated to the wider sample or population you are investigating. Does the sample represent the wider population? Are the sampling methods appropriate? Random selection is the most experimentally sound way to recruit participants and assign them to groups.

- **Social desirability bias-** as in the example above, this can occur when people complete surveys in a way that would be viewed 'favourably' by others: either over or under-reporting. It is important to keep this in mind when carrying out surveys, to ensure your data is valid.

- **Statistical conclusion validity**- The extent to which conclusions made about relationships between variables are reasonable. This is affected by sample size and internal validity.

- For example, it may be that there is an effect of X intervention but you didn't find it because the measurement tool was not reliable or your sample wasn't big enough i.e. you didn't have enough *statistical power*.
- Conversely, you could conclude a significant effect of X intervention which probability-wise may have been a fluke! Statistical significance levels are important here, which in psychology often assume a 0.05 level of significance. In other words, for every time you run a statistical analysis you would expect the result to happen by chance 5 times out of every 100 statistical tests. Therefore, the more independent statistical tests you do the more likely it is you will eventually turn up something significant! Playing with the data and 'phishing' for results by doing many independent tests will affect the statistical conclusion validity of your results and should be adjusted for

The relationship between reliability and validity

For data to be valid it must also be reliable, for example, if people received a wildly different score on an intelligence test every time they took it, the test is unlikely to be able to predict anything and is therefore would have no **internal validity**.

However if a test is reliable it **does not** mean it's valid. For example, a simple measure of heart rate (beats per minute) might be very reliable physical measurement, but it does not necessarily mean it is a valid predictor of wellbeing. To be valid there has to be evidence that it measures what you want it to.

2.2 Ethics considerations

In any research there are ethical considerations to bear in mind and data should be collected responsibly. Good research depends on mutual trust and respect between investigators and participants, maximising benefits and minimising harm.

Wellbeing data collection can be considered a form of social research or enquiry and appropriate ethical guidelines should be consulted. There are several bodies who have published guidelines for good practice, namely the BPS (British Psychological Society), and SRA (Social Research Association). You can find their documents **here.**

The main principles of ethical research centre around: protecting participants from harm, ensuring good standards of scientific methods of data collection and analysis and fair interpretation of and dissemination of findings.

Risk of harm

- In all social research, the risk of harm to individuals, groups and wider society should always be considered in the design of data collection methods, analysis and reporting.
- Although the motivation and agenda to collect wellbeing data will differ wildly between projects, it is the responsibility of the researcher to consider the consequences of research no matter how small the project.
- There is no absolute formula to predict the likely risk of social enquiry but researchers should consider all potential risks. Researchers are responsible for respecting and protecting the rights, dignity, privacy and self-determination of all participants.

Informed consent and right to withdraw

- Participants should be fully informed of the processes of data collection, analysis and reporting and their involvement should be fully voluntary.
- They should be made aware that they can withdraw at any time and that withdrawal would not affect them adversely in any way.
- Participants should be given opportunity to understand what they are being asked to do and have ample time to give their informed consent. It is good practice to provide written information sheets and consent forms.

Inclusion

- No group or individual should be disadvantaged from being consistently missed out or under-represented.
- Good quality research depends on gathering reliable and valid data that represents the people affected by the findings.

Data protection

- All identifiable data should be collected, stored and destroyed in line with data protection legislation. There are different rules depending on whether the data is considered 'personal sensitive data', which wellbeing data often is. See data protection legislation **here.**
- Participants should be made aware of how their data is stored, whether it will be held and analysed anonymously or just confidentially. They should also be made aware of how the data is going to be used and reported.

Confidentiality

- Participants should have confirmation that personal information will remain confidential. This is especially relevant in qualitative research where sensitive and personal topics are discussed in depth.
- Participants should be confident that their data will remain confidential, as any doubts about this could bias the responses they give.

Conflict of interest and objectivity

- If you are collecting data within an organisation that both yourself and your participants belong to, your dual-role may create a conflict of interest. All information can be misunderstood or misused and the potential harm to individuals or groups by obtaining data and reporting findings should always be considered and mitigated as much as possible.
- For example, findings reported from a small wellbeing study within a workplace may mean certain groups are stereotyped for having particularly 'low wellbeing' and decisions made on the basis of this may mean that people given preferential treatment over other employees as a result. Be responsible when reporting the limitations of your findings, acknowledging any shortfalls in data collection or analysis.
- It is important to be as transparent as you can about the motivations and objectives for data collection and remain impartial as much as possible. Although no research can be completely objective, researchers should pursue objectivity wherever possible. This means being honest about your own opinions and agendas for conducting research and your subjective interpretations of the data.
- Your participants may make assumptions about the reasons for data collection if you do not make this clear. Consequently, the data you collect may not be reliable if your participants feel they need to respond favourably towards you or your organisation or if they feel they are being personally evaluated.
- Participants should be made aware of how they may benefit from the research findings, and any conflicts of interest should be discussed before data collection.

2.3 What do you want to find out?

Choosing a research question

Your research question refers to what you want to find out, and is the driving force of your whole research project. It guides your method of data collection, analysis and interpretation of the results.

The question should be:

- Clear
- Something you (and/or your organisation) are interested in
- Be appropriate for the topic
- Sensitive to relevant research in this area

Following the steps below by filling in the boxes should help you generate an appropriate research question:

What do you want to find out?	**Answer**
Identify a broad area for investigation *e.g. Wellbeing. This is the general area, but cannot be the whole driving force for the research. Once you have a general topic e.g. 'the impact of monthly social events on staff wellbeing', you can get more specific.*	
What has already been done in this area? *Get familiar with wellbeing measurement e.g. ONS wellbeing survey, Happiness Pulse, qualitative interviews that allow you to explore wellbeing in the workplace.*	

Narrow down your topic: Ask yourself some open-questions like how, how much, why? Think about the factors that might contribute to the topic and what you are interested in. It needs to be a question! *e.g. How is the wellbeing of my employees affected by social-contact at lunchtime?*	
What sort of data do you want? *Are you interested in breadth of information (quantitative) or do you want depth (qualitative)?* *Are you looking for numbers or stories?*	
Is it possible to get the data you want? Can you measure it the way you want to? *e.g. How will you 'measure' wellbeing? Are you interested in comparing wellbeing scores or getting insight into how individual's experience wellbeing? How will you measure social contact? What tools will you use? What tools have other people used? Is your preferred method reliable/valid?*	
Is it feasible to get the information you want? *I.e. Do you have the resources, time and expertise to carry out the research?*	

Will the research produce data that can be supported or contradicted? *I.e. It is possible to compare the data to other data sets? Does it relate to a scientific theory? Are you interested in a universal reality or the unique perspective of individuals?*	
Is the question too broad/too narrow? *I.e. Is it too difficult to answer the question? Is it vague or too general?*	

2.4 What kind of data will answer your research question?

Now you have some ideas about the research question you want to answer, you may have a better idea of whether you would like to collect quantitative or qualitative data (or even both!).

What is quantitative data?

- Information that can be expressed statistically or in numerical form
- Assumes a fixed and measurable reality
- Concerned with discovering facts about certain social phenomena
- Can offer breadth of information
- Can broadly generalise findings to similar groups
- Limited in depth and detail

What is qualitative data?

- Typically descriptive data
- Often more difficult to analyse that quantitative data
- Concerned with understanding behaviour from the individual's perspective

- Assumes a more dynamic state of reality
- Offers depth of information
- Often unable to generalise findings beyond individuals who provided the data

As you can see, there is generally a breadth versus depth trade-off between quantitative and qualitative data and subsequently the extent to which you are able to generalise your findings.

To illustrate this point consider the following example:

- *Wellbeing intervention*: a group of volunteers have created an allotment in your community that allows people to plant and pick vegetables

- *The volunteers want to find out:* gender differences of those people in the community that used the allotment and those that didn't

Quantitative or qualitative data?

- A *quantitative* wellbeing questionnaire completed by all members of the community would give you broadly representative data about the different groups that used the allotment (or not) and a general understanding of gender differences amongst respondents e.g. 35% women, 65% men used the allotment in the first week. You could broadly generalise these findings to the local community providing you had a representative sample. However, these responses would probably provide superficial or limited data on gender differences at best.
- Conducting smaller focus groups (a *qualitative* technique similar to a group interview) within the community, possibly breaking groups up according to gender or allotment-use, offers a much richer source of data on the role of gender in people's choice to use the allotment. For example, you could discover that some women didn't use the allotment because: they don't enjoy planting vegetables, they already visit an allotment outside the city, or because they would rather visit the local park in their spare time. However, these more detailed responses would be less representative of the wider community and may only be relevant for participants of the focus groups.

Quantitative data is good at answering these sorts of questions:

- How many people in the organisation took the wellbeing survey?
- What is the average wellbeing score for my organisation?
- What is the life satisfaction score for members of my organisation on a scale of 1-6?

Quantitative data is **not** as useful when trying to explain the 'Why' behind the 'What' such as:

- Why did person X choose to not take the wellbeing survey?
- Why does the average wellbeing score vary so much within my organisation?
- Why is the life satisfaction score of this team higher than the life satisfaction score of this team?

To get the answers to these questions you may need to explore alternative qualitative methods of data collection to get a deeper understanding of wellbeing and wellbeing measurement in your organisation.

For more detailed information on methods for qualitative data collection see **this guide.**

2.5 Quantitative research questions

If quantitative data is the best source of information to answer your research question, the following examples illustrate some pitfalls of poorly-constructed questions and how you might avoid them:

Too broad/unfocused: *How does low wellbeing affect people's lives?* 'Affect people's lives' could mean many things. How are you going to measure this? If you want quantitative data, you need to think about how you will measure wellbeing, and the impact of 'low wellbeing'. You might need to read up on other factors important in wellbeing to focus your question.	**More focused:** *How do average wellbeing scores correlate with physical activity levels amongst members of my organisation?* This clarifies how you will measure wellbeing (scores/averages), and you are focusing on a specific factor linked to wellbeing (physical activity). You would need to define how you measure physical activity (e.g. how many hours per week do you…?). However, both wellbeing and physical activity provide quantitative data you can compare.
Too narrow: *How many more times did this person complete 15 minutes of cardio exercise after X wellbeing intervention than before the intervention on Friday afternoons?*	**Broader:** *Did people do more/less exercise after X wellbeing intervention compared to before?*

Here you are really limiting the scope of your research and it may be very difficult to find out the answer to this question without very specific and accurate numerical data. 'Cardio' limits the question further, and it's definition would be different for each individual. You would need to provide a rationale for looking at 'cardio exercise' specifically in relation to wellbeing.	This question has the same focus on the relationship between exercise and a wellbeing intervention but is more easily measured. It also provides more scope to interpret and discuss the findings as there is lots of research exploring the relationship between exercise and wellbeing.
Unresearchable: *How will X wellbeing intervention affect academic performance of participants' children in the future?* Getting answers to broad questions about academic performance in the future is not possible unless you are planning to do a well-designed longitudinal project. It would also be incredibly hard to research this topic meaningfully. Looking at data of people who are not participants of the intervention you are researching would be scientifically complex and bring many ethical issues.	**Researchable:** *Do the exam results of students' who received X wellbeing intervention results differ from those who did not receive X wellbeing intervention?* Firstly, this question can be answered in the present. Here you are clearly clarifying a variable you want to measure- exam results. The participants are from different groups but you are comparing them meaningfully.
Too many questions: *What are the differences between wellbeing scores of men and women and what is the impact of the staff wellbeing policy on the wellbeing scores of staff?* There are two questions here. Although you may be interested in both, they should be thought of as separate research questions. If you are unclear about your overall goal, you could find you have too much to do, your data collection process is ineffective and your analysis and reporting is	**Researchable:** *What are the differences between wellbeing scores of men and women* *What is the impact of the staff wellbeing policy on the wellbeing scores of staff?* Separate into two questions

unfocused and confusing.	
Needs qualitative data: *What is the content of people's conversations about wellbeing?* This question cannot be answered with numerical data.	See **this guide** for qualitative data-collection.

2.6 Selecting your sample: size and population

Sample size

If you are collecting quantitative survey data, the amount of respondents will affect the validity of your conclusions. It is generally good practice to get as bigger a sample as you can and if the survey is voluntary, be realistic in predicting response-rate.

For example, consider this wellbeing intervention:

- *Intervention:* a company director organises a tea and cake party every second Friday in the workplace to improve wellbeing
- *Measurement of intervention success:* asking two individuals out of two hundred staff members to complete a 'before and after' wellbeing survey

This would **not** be a reliable dataset to draw conclusions from. The **population validity** of our dataset is low because we have a very small unrepresentative sample, therefore findings cannot be confidently extrapolated to the wider workforce. If both of those people responded that their wellbeing had not improved as a result of the tea and cake intervention, could you confidently say that the other 198 people had not benefitted from this intervention?

In addition, the (statistical) **conclusion validity** would be low when analysing the data as we have low statistical power. That is, we have not collected enough information to determine whether the impact of tea and cake on wellbeing in the workforce is greater than what we would expect by chance. If we have more data points, we can be more precise about our estimates of wellbeing in the workforce.

There will always be confounding factors that contribute to your findings such as whether certain people work on a Friday, if they even drink tea or whether they have a gluten intolerance and can't actually eat the cakes. Therefore, the bigger your sample, the more likely it is that you will get representative data from which to make valid conclusions. Essentially it's a numbers game, the more tea and cake eaters taking the survey, the more likely it is that the average wellbeing score of the workplace won't be skewed by those individual factors. In other words, you will have a better understanding of the success of the intervention if you ask as many people who took part as possible.

Sample population

The **population** is the group of people you are trying to understand. This could be everyone in your community, female members of your organisation, or people who own boats in Bristol Harbourside. Therefore, when collecting and analysing your data, it is important to know how *representative* your sample is of the wider population that you are interested in. Data is representative if it is *typical* of that group or population. This dictates the extent to which you can reliably make meaningful conclusions about a population wider than your sample.

For example, consider this wellbeing intervention:

- *Intervention*: a one-time community street party to improve intergenerational contact (a key factor in wellbeing)
- *Measurement of intervention success*: a wellbeing survey sent to all members of the community
- *Response rate:* 75% of the community responded to the survey saying that the street party had significantly improved their wellbeing. However, there were no respondents aged 16-25

At first glance this is an excellent response rate! It also looks like the street party was a success for 75% of the community. However 25% did not complete the survey and of those, there were no respondents aged between 16-25. It may be that there are no 16-25 year olds in the community, but this would be very unusual (there may be statistics available from your local authority that tells you the proportion of people aged 16-25 within a given geographical area).

Let's say for this community, you knew that roughly 20% of the population were aged 16-25 . You essentially have no data for 20% of the community, and therefore the sample of surveys you received back is not representative of the whole community.

It may be for these individuals their wellbeing didn’t improve because; they attended a different event in the city that day, they didn’t feel welcome, or maybe this age group didn’t want to complete the survey. Whatever the reasons, you cannot conclude that the street party successfully improved the wellbeing of the **whole** community, as the sample was not representative of the population you are interested in.

3.0 Wellbeing: quantitative data collection methods

The method of data collection should be guided by your research question. Some examples of quantitative research questions are:

- How does the wellbeing of my organisation compare to national averages?

- Has the wellbeing of my organisation improved as a result of X wellbeing intervention?

- In what areas of wellbeing are my staff doing more or less well in? (E.g. life satisfaction, sense of purpose etc)

These questions can be answered by quantitative data because the data can be expressed in statistical or numerical form.

3.1 Wellbeing questionnaires and surveys

A primary method of collecting wellbeing data is through questionnaires, which could be completed via email, survey monkey or other on-line ways, or hard-copy. Surveys are a good way of collecting lots of wellbeing data at once in a standardised way.

We have provided a list of established and validated wellbeing questionnaires that are compatible with our WellWorth tool which you can access **here**.

When planning a questionnaire it is important to consider:

- *Resources for data collection and analysis*- some methods take considerably longer. For example, if you have a team of 200 people it may be difficult to print out 200 different wellbeing questionnaires which are then returned by post and need to be analysed manually. Staff power, time and know-how are all important factors to consider. Capturing data electronically would be a more efficient, resource-light way of collecting this data (**see Online Surveys**).

- *Human error*- Especially with large amounts of data, the more you can reduce the probability of human error when you are moving data around, the better. If you can input data electronically from the beginning you can be more confident that the data is reliable and avoid lengthy data-verification processes that come with entering data onto a computer from paper questionnaires.

- *Standardisation*- It is rarely possible to conduct highly controlled experiments, allocating participants randomly to groups, using control groups and minimising any external or confounding variables that may unevenly influence data collection. However, you can still standardise all of your procedures and materials as best you can. Minimising differences in participants experiences and environments when collecting data will ensure a broadly equivalent experiences and allow more valid comparison between or within participants. Provide all of the same materials, preferably at the same time of day in the same place and try to reduce any external factors such as noise, discomfort or social desirability bias.

Designing your own questionnaire

If you wish to design your own wellbeing survey, the design of your questionnaire will be guided by the sort of data you want to get. The table below summarises what sort of questions and response types fit together and what sort of data you can expect back (Fig.1).

Types of question	What sort of data do you get?	What are these good for?	Advantages/Disadvantages
Dichotomous questions (closed)	Numerical, nominal	Yes/No, Agree/Disagree, True/False **E.g. Do you live in the UK? Yes/No**	**Limited:** A very small amount of differentiation between the two responses, only appropriate for some questions **Speedy:** Data is easy to code and interpret
Likert Scale (closed)	Numerical, ordinal	Where there are levels of measurement that represent ordered categories. Good for opinions, attitudes, frequency and importance e.g. Rating levels of agreement. **e.g. Strongly agree>Somewhat agree>Neutral>Somewhat disagree>Strongly disagree**	**Restrictive:** People may feel they belong to a number of categories. Also if using an even number of questions you are making someone choose what side they sit on- this is a **forced question.** It is generally good practice to have an odd number of categories so respondents can answer neutrally. **Subjective:** If you are creating the response categories, the 'difference' between levels will be decided by the participant. Scaling is not objective like for example, centimetres on a ruler. If there is no objective measure, interpretation of the scale will vary. **Greater range of data:** Offers more interesting data than dichotomous questions
Slider scale (closed)	Numerical, interval	Where there are bi-polar ends of a spectrum and participants can score where they lie between the two. Different to likert in that participants can rate where they feel they sit on a scale rather than assigning themselves to category **E.g. How would you evaluate X wellbeing intervention on a scale of 1- 10 where 1=Poor, and 10=Excellent?**	**Subjective:** If you are creating the response categories, the 'difference' between levels will be decided by the participant **Spectrum confusion:** Bi-polar responses may not always be appropriate E.g. On a slider scale where Happy=1, and Sad=10, If someone felt a bit sad on a given day, could they also have felt a bit happy too? Would somewhere in the middle be a true answer in this case? **Richness:** It's an economical way to get more precise information about participants than likert scales

Types of question	**What sort of data do you get?**	**What are these good for?**	**Advantages/Disadvantages**
Ranking (closed)	Numerical	When you are asking someone to rate the order of preference or importance **E.g. Rank in order of importance these activities are to your wellbeing**: Exercise_**1** Socialising_**3** Cooking _**2**	**Confusing:** Participants might not understand the ranking system we are looking for if not clear- which could mean unreliable data. **Good for estimating value:** Can give some indication of 'value' people place on things- important in a lot of wellbeing research
Filter or contingency (closed)	Numerical, nominal	Filters and contingency questions will generally be dichotomous e.g. Yes/No. You would use these to confirm the participant is eligible to answer the next question. **E.g. Q.1A) Do you currently own a car?** **If Yes- Proceed to Q.1B) How often do you drive it?** **If No- Proceed to Q.2A)**	**Complicated:** Having too many levels in a question can confuse the respondent especially if they have to jump pages. They might not continue with the questionnaire if it feels to laborious. Try to avoid more than 3 levels in any filter. **Economical use of time:** If used well this can be a more economical use of participants time if they don't have to answer questions that don't apply to them.
Open-questions	Descriptive data, text.	Qualitative studies see **here**	**Difficult to analyse**: need to be coded numerically to analyse using quantitative methods. **Offers depth of information:** Allows respondents to answer in their own words in richer detail

Further tips for designing questionnaires

- **Length-** Questionnaires should be as brief as possible. Questions themselves should also be phrased concisely and simply. Participants are likely to get bored filling out lengthy questionnaires or reading questions that are wooly or overly long. Engagement of participants is important to gather reliable data.
- **Structure-** Just like in an interview the questions should follow the structure of Introduction->Main Body->Conclusion. Begin with outlining the purpose of the questionnaire and anything relevant to consent/taking part and confidentiality etc (See **ethics**). Transition from topics in the main body of the questionnaire are helpful e.g. "The next set of questions will ask you about…". You should conclude by thanking the participants for their time, reiterating confidentiality and providing your contact details.
- **Purpose-** Only ask questions that are relevant to your research. You may end up with data that is irrelevant or it may mean participants disengage if you are asking lots of questions that appear random or unnecessary.
- **Subjective questions-** Begin with more objective questions if possible, moving into subjective ones. Demographics should be asked at the end or provided as a written form.
- **An option for 'Other'-** Where appropriate ensure that there is an option for 'Not Applicable' or 'Other' if the categories you have listed are not exhaustive. It gives people the choice to answer accurately and increase the reliability/validity of your data.

3.2 Creating mobile or web surveys

Collecting wellbeing data via new or existing mobile apps may not be relevant if you simply want to capitalise on the technology and accessibility of mobile phones, tablets and computers to administer a straightforward wellbeing survey. They offer distinct advantages over paper questionnaires in terms of greater accuracy, ease of administration and even cost for larger or more geographically-spread surveys.

Mobile-app versus mobile-optimised

You may want to create a mobile application that is available to download via the iPhone or Android app-store. Using a web-based survey means those with phones can equally access the survey via the internet.There are pros and cons to designing surveys as mobile apps, or web surveys which can be optimised for mobiles.

Here are some basic differences:

- **Mobile surveys can be restrictive:** If your application is limited to mobile phones (Android/iPhone), your data collection will be limited to those who own these devices. If the survey is online, your sample is inclusive of anyone with access to the internet via a laptop, tablet or mobile phone.
- **Response rates and cultural variation:** Some people have found response rates for mobile phone surveys are lower than web-based ones. This will obviously depend on your sample. There are cultural variations in how people use mobile devices, how knowledgeable they are about mobile apps and how comfortable they feel using them.
- **Notifications**: if you are interested in gathering data over time using experience sampling (in-the-moment assessments), mobile phones offer greater capability to send notifications to the user asking them to complete surveys about how they feel in the moment. Many people are used to checking their emails, social media feeds or text messages regularly and so a short survey might not feel too disruptive.
- **Design constraints:** The design features of mobile phone apps can be more constrained than web surveys, such as navigation buttons and checkboxes which might be important for measurement.
- **Boredom and irritation:** receiving notifications and alerts on your mobile to fill out momentary assessments of wellbeing can be irritating and feel intrusive. Respondents may also be reluctant to complete assessments that feel too long. This can lead to unreliable or inconsistent data collection.
- **Engagement:** Problems with boredom and irritation synonymous with data-collection via survey tools can be minimised by introducing 'engagement' functions, like feedback or personalised graphs. Users can be incentivised if there is the benefit of self-knowledge.
- **Battery zapping:** Users can be switched off by mobile apps if they are a drain on battery or internal memory.

Costs

There are many platforms that offer packages which allow you to create surveys for free, or within a 'free trial period'. Digital developers provide more extensive (expensive) packages or annual prescriptions to create more bespoke survey applications with additional functions, analysis or reporting power.

If you are looking to gather data via repeated surveys it may get pricey, as many developers cost their work on a survey-by-survey basis. Mobile apps in particular can capitalise on repeated data-collection methods, so this is something to bare in mind if you want more than a one-off survey.

Mobile and online survey market

These types of survey platforms are most commonly used for consumer-research, but can also be useful for wellbeing data collection. For most sites there are both template and custom options. Below are a list of the most reputable and well-known digital platforms for creating web and mobile surveys.

PollDaddy	Online survey software with powerful reporting functions (free accounts available) https://polldaddy.com/
Survey Monkey	Online survey software with high customer satisfaction ratings (free accounts available) https://www.surveymonkey.com/
Pocket Survey	Surveys for Android/iPhone's- choose from over 50 question types (7 day free trial available) http://www.pocketsurvey.net/
Survey Analytics	Online survey suite of tools for collecting and analysing data. Good for complex questions (14 day free trial available) https://www.surveyanalytics.com/mobile/
Zoomerang	Online software to create surveys fast. Access to lots of free templates (free packages available) http://www.zoomerang.com/
SurveySwipe	Mobile survey app- allows you to get real-time data (free trial available) https://www.getapp.com/customer-management-software/a/surveyswipe/

CASE STUDY A city-wide wellbeing survey

The 'Happiness Pulse'

In the next section we explore a real-life example of using an online wellbeing survey. Happy City developed an online survey measurement tool- *The Happiness Pulse*- to gather valuable data on the wellbeing of people in Bristol from April-July 2016.

Below we have outlined our Happiness Pulse 2016 pilot to share our learning with you about collecting quantitative wellbeing data in this way.

Developing an online survey tool

The Happiness Pulse survey tool consists of 20 questions about personal wellbeing (life satisfaction, sense of purpose etc.) and 10 optional questions related to the drivers of wellbeing (conditions that promote wellbeing such as employment, health etc). You can take your Happiness Pulse **here.**

Domains and items on the Happiness Pulse were selected through a review of the academic literature and a stakeholder engagement process, including local policy makers, community organisations and individuals. Three domains of wellbeing were identified: Being, Doing and Connecting. The Happiness Pulse is designed to be a wellbeing health-check that could be taken just once, several times of the course of a few months or as a before-and-after impact evaluation of projects and interventions.

Our measure of Happiness

The Happiness Pulse was a composite measure made up of 7 questions from established surveys ONS Life Satisfaction questions and SWEMWBS mental health scale and 13 new items. Click **here** to see our list of established and validated measures of wellbeing

A further 5 demographic and 10 'City Pulse' questions were also asked- these were optional. 'City Pulse' questions referred to the respondents living conditions, and related to key policy areas of Work, Health, Education, Place, Culture.

Getting people to take their Happiness Pulse

We experimented with a novel recruitment approach to gather representative ward-level data about the people in Bristol. Gathering representative city-wide data is very difficult if you don't have the contact details of everyone in the city, so we aimed to capitalise on certain channels of communication to spread the word about the Happiness Pulse.

To access as broad a sample as possible of people in Bristol we used a combination of communication and partnership strategies:

- **Partnership strategy**- We worked with umbrella organisations in key sectors across Bristol (Health, Voluntary, Culture, Business, Environment) who would promote the Happiness Pulse to their members and staff. We offered them a unique URL and code which allowed them to collect wellbeing data specifically within their organisation. After the trial, we provided them with the Happiness Pulse data for their organisation. This provided a mutual benefit of wellbeing data-collection. This is a unique cross-sector strategy, which won't be relevant if you are collecting data specifically within a group or organisation.

- **Communications strategy-** We launched city-wide PR and social media campaigns which involved radio and TV coverage, blog posts and mass emails to partners and friends of Happy City. If you have access to broadcasters, a strong social media presence or a powerful internal communications department this can be an effective way to raise awareness of a wellbeing survey.

The Engagement Factor

The Happiness Pulse online tool was created by digital developers SimpleWeb with the aim of providing an engaging alternative to more extractive measures of wellbeing that fail to include users in the process of gathering and understanding their own wellbeing data. Stimulating graphic designs, explanations, tips and links aimed to offer an engaging and rewarding experience for Pulse-takers.

The Happiness Pulse provides individuals their results and feedback on their data. 'Explore More' pages are available for those who wish to learn more about their wellbeing, and there are sharing options for social media. This type of online survey offers many advantages over generic surveys but costs a lot more than open source options like SurveyMonkey.

How is the Happiness Pulse data useful for people in Bristol?

- **Benefit to individuals and organisations:** We have received huge amounts of positive feedback from individuals who took the Pulse and organisations that promoted the Pulse to their staff. Putting wellbeing on the agenda and gaining a better understanding of our personal wellbeing and what we can do to improve it has intrinsic value: measuring what matters to us.

- **Relevance to local policy**- Happy City is interested in how measures of urban wellbeing can impact local policy. Additional demographic and geographical data collected by the Happiness Pulse and the 'City Pulse' questions could provide highly relevant data about where wellbeing is high and for whom. This sort of ward-level data could be very influential in local policy, putting the wellbeing of Bristol people at the heart of local decision making.

- **Comparison to national averages-** Because the Happiness Pulse includes national measures of wellbeing (ONS life satisfaction questions and SWEMWBS mental health scale), this means these composite measures in the Happiness Pulse can be taken out and compared to other national datasets.

3.3 Analysis tools for quantitative data

Depending on how much data you have and the detail of analysis you wish to carry out your methods for analysis will be different. If you do not want to pay for software there is free software available (such as Apache Open Office, Libre Office etc) which can hold datasets in text/spreadsheet/CSV format, but programs can differ in terms of their capabilities to create graphs and analyse data.

Descriptive statistics

Descriptive statistics refers to how you display or show the data in a meaningful way, for example to show trends or comparisons. This is essentially summarising your data. You may choose to create a straightforward graph using Microsoft Excel or Google Sheets and guidance on visualising simple graphs is generally provided on the web.

Statistical tests

The type of data you collect i.e. ordinal, interval etc., will dictate the range of statistical tests you can use and the reliability and validity of your results. In addition, the dataset you have may need to pass certain tests or 'assumptions' for the test to be considered valid such as, sample size or verifying whether the data is 'normally distributed'.

Some statistical tests are available in software such as Microsoft Excel (t-tests, z-tests, correlation etc.) but for very complex analysis you may require a more sophisticated statistical package. There can be expensive subscriptions with this type of software (e.g. SPSS) which are probably not appropriate for a one-time analysis. Free statistical software (e.g. 'R') are available to download, but can be less 'user-friendly' and may take time to get to grips with (see our list of **useful links** for available statistical software packages).

3.4 Big data

What is 'big data'?

An alternative or additional method of assessing wellbeing patterns or trends is by accessing 'big data'. Big data is a term used to describe very large or complex data sets that traditional methods of analysis may be inadequate to fully understand. Social-media mining is one way to access this data and essentially involves 'mining' into data sets available on the internet. This method of data collection is gaining increasing interest from research bodies and commercial organisations wanting to capitalise on data available in the public domain.

Twitter, Facebook and Google are among the top sites that people are collecting data via. On Twitter for example, you can stream tweets from a certain geographical area over a specific time period, or collect all tweets containing the word 'wellbeing' by searching for keywords. The collection process can be tricky if you do not have computer-programming know-how within your organisation. However, for many competent programmers, creating computer applications that collect this type of data can be a relatively straightforward task.

How can big data be useful?

Collecting wellbeing information alongside geographical and real-time data from mobile apps or social media provides unprecedented opportunities for data-driven innovation in cities.

Combining data collected on 'states' and 'flow' in cities and the wellbeing correlates of transport patterns, employment statistics and access to housing can be used to improve the efficiency of urban systems and promote wellbeing-focused policy. The increasing availability of this sort of 'big data' allows us an incredible level of granularity of information which can inform targeted interventions in cities.

Big data can answer these sorts of questions:

- What are people chatting about (and is it valuable)?

- How happy are the people of Bristol on a Tuesday morning compared to a Saturday morning?
- Do trends in wellbeing vary with traffic conditions, weather, world news?
- How happy were tweets in the UK before and after the EU referendum?

Happy Tweets

Happy City conducted a Twitter big-data trial this year, to better understand the benefits and limitations of this sort of quantitative data. Twitter is an online social networking service that allows users to send and read 140-character messages called 'tweets'. Registered users can read and post tweets, whereas unregistered users can only read them. We chose to focus on Twitter due to the openness for public consumption, appeal to users from all walks of life and the fact that tweets can happen in real-time, often capturing people's thoughts on a moment-to-moment basis. See the more detailed case study on page 35.

Twitter data can represent the broadest cross-section of society and is more complex and multi-faceted than you might think! Tweets and Twitter's 'following' function, means people are linked in a variety of ways from brief conversations to 'interest graphs' that connect people based on the things they care about. Twitter is more appropriate for collecting **social wellbeing** data, rather than subjective wellbeing data (of individuals). **Social wellbeing** relates to social and income equality, social capital, social trust, social connectedness and social networks and has direct implications for both subjective wellbeing and mental health. **http://www.fph.org.uk/concepts_of_mental_and_social_wellbeing . *****

Where do I start?

- *Speaking the language: y*ou will need to write some **source code**. This is a set of instructions for your computer that tells it what to do. This is generally in a human-readable format (probably text) and comes in a multitude of forms e.g. Python, Ruby and C#. You can learn to write code, but for a complete beginner this will take considerable time. Alternatively, you can hire a web developer to do this for you, but their time can be very expensive.
- *Setting up your software environment*: if you plan to use your own computer, you will need to research what software (programs and operating information used by your computer) is required to set up the infrastructure for your big data program. There are many guides and online tutorials out there, which can tell you what you need to get started- (**link to list here**)
- *Create a Twitter account*: you need an account to create a Twitter application here- https://dev.twitter.com/apps - that can make API (Application

Programming Interface) requests to Twitter. Basically API's are a set of functions and protocols that allow you to create a software application. Once *you* have created *your* app- this will authorize access to *your* account data.
- *Develop your app:* you create your own **'virtual machine'** using **source code**. This is a software computer (one you can't touch) that like a physical computer, runs on an operating system and applications. The virtual machine is made up of a set of specification and configuration files running on the physical resources of a host computer.

Streaming or Searching?

You then need to decide how you want to access Twitter data. There are two main ways to access Twitter- the Search API and the Streaming API.

- **Twitter's Search API**: gives you access to a data set that already exists from tweets that have already been tweeted. You can request tweets that match some sort of "search" criteria such as: keywords, usernames, locations, named places, etc.
- **Twitter's Streaming API:** is a push of data as tweets happen in near real-time. You can register a set of criteria (keywords, usernames, locations, named places, etc.) and as tweets match the criteria, they are pushed directly to you through your own stream.
- **Storage**: you need somewhere to store your tweets. In your source code you can tell the application where to store the tweets coming in, Mongo DB and Couche DB are some examples of free and open-source databases suitable for storing Twitter data. You can set up Twitter programs via a web server, which means it can run when your computer is switched off. Data can then be downloaded at a later stage from a web browser.
- List of useful links

How do you make sense of big data?

Big-data can be very complex and difficult to analyse using traditional methods, so some things to have in mind are:

- **Twitter data can be messy, and there is lots of it**: Tweets not only contain the 140 character text we see on screen, but loads of information about when the tweet was tweeted, details about the user, location, time/date etc. You probably don't want or need all of this information so some pruning of the data will be necessary to get to the 'juicy' bits. In addition, to analyse Twitter data you'll need to get it in the right format (ideally Excel or csv).

- **Length of time and amount of tweets collected:** Although you can collect thousands of tweets very quickly you might need to do this over a significant amount of time to gather meaningful data i.e. that is valid and reliable. If you are collecting tweets for a long period of time, that is potentially a lot of data you are accumulating which (if you are using one computer) may put a strain on your computer's internal memory. Knowing how much data, and for how long you want to collect data is important to account for additional data-storage costs, such as external hard-drives or online cloud-storage.

- **Wellbeing and sentiment analysis:** (or 'opinion mining') refers to natural language processing, text analysis and computational linguistics to find and pull-out subjective information in big data. This is one way to analyse tweets, and may require purchasing a sophisticated sentiment analysis dictionary which you can then load tweets into (in the form of a csv/Excel file/text file). Open source dictionaries are available but products vary in quality. Words and the structure of sentences can have emotional qualities, which can be categorised into positive and negative affect (e.g. happy versus angry words). A sentiment analysis dictionary processes the text from tweets and can tell you (amongst many other things) the sentiment of them- i.e. the emotional or affective quality.
  - For example, the tweet - "I am very happy today, hooray for wellbeing!"- would probably give quite a high 'positive-affect' score. Whereas- "I'm so miserable- BOO for rain!"- would give a relatively lower 'positive-affect' score and potentially quite a high 'negative-affect' score!

CASE STUDY: Happy City Twitter Trial

We chose to gather wellbeing data specifically from Bristol via a big-data Twitter trial. Around 2-5% of individuals enable GPS on their mobile devices which allows us to filter the exact location of tweets that could provide interesting ward-level data. It is also possible to gather city-wide data by streaming tweets of users with their place of residence set to 'Bristol'. We chose to use the Twitter streaming API to capitalise on the real-time nature of tweets, and streamed tweets from the Bristol area using a 'bounding box' (a set of coordinates in the source code that detects and streams tweets from a geographically defined area). Due to the technical nature of building a Twitter application, this guide will not be an exhaustive review of creating the app but summarise what we did, how we did it, and what we found.

What we wanted to find out:

At a basic level we were interested in the feasibility of setting up a big data trial, due to the technical expertise required to set up, conduct and analyse big data.

1. *Feasibility:* How easy and costly it is to collect city wellbeing data via Twitter? How much? What level?
2. *Data*: How representative is the data collected? What are the potential research findings from this data?
3. *Engagement:* How can individuals and other stakeholders (organisations, local authorities) be engaged using this data?

What we did:

Following the steps outlined above, we created a Twitter application on a computer in the Happiness Hub which took one part-time staff member 3-4 months to set up (whilst also working on other things). The application streamed tweets around 60 miles from the centre of Bristol, so tweets outside of Bristol were filtered retrospectively (*NB. If using a geographical bounding box it is good to check your longitude, latitude coordinates are in the right order!).*

Within our team there was no one with the computer-programming expertise required to set up the trial and we relied on pro bono support from partners and friends of Happy City, online tutorials and 'social-media mining' books.

IT resources

- *Hardware:* ASUS Zenbook laptop
- *Operating system*: Windows 10
- *Source code environment*: Anaconda (Jupyter Notebook)
- *Source code language*: Python
- *Storage:* Mongo DB and external hard drive
- *Sentiment analysis:* LIWC sentiment analysis dictionary (software)
- *Other analysis:* Windows Excel and R (statistical software)
- *Textbook resource*: Mining the Social Web (2nd Edition)- Matthew A. Russell

Sentiment analysis

In addition, we had some basic research questions about the positive/negative emotions of people tweeting in Bristol.

1. How effective is the LIWC sentiment dictionary at analysing tweets?
2. Are there any trends for positive/negative affect for Bristol people at different times of day/month?
3. What is the impact of the EU referendum on the wellbeing of Bristol residents?

This was the sentiment analysis aspect of the trial, which could inform our understanding of the benefits and limitations of analysing twitter data in this way. These findings will form part of a more detailed report available in October 2016.

LIWC dictionary

The **L**inguistic **I**nquiry and **W**ord **C**ount (LIWC) program analyses text (in our case tweets) and counts the percentage of words that reflect different emotions, concepts and other categories. For the purposes of our small scale trial we mainly focused on positive and negative affect, but the dictionary has the capacity to categorise words into many other psychologically relevant domains such as: use of pronouns, social concerns and time orientation.

LIWC was developed by researchers with interests in social, clinical, health, and cognitive psychology to better understand links between our words and minds. Language categories aim to capture people's social and psychological states and the master dictionary currently holds 6,400 sentiment sensitive words.

Many words fall under several categories and the creators acknowledge that while their instrument may be crude, the program operates on 'probablistic models of language'. In other words, although the dictionary analyses words in isolation such as 'good', if the overall intention and context of a tweet was negative, the dictionary would pick up on higher rates of negative words. Generally speaking, conclusions drawn from the data are not heavily impacted by these kinds of classification errors because of the ways we use language.

The more data you have the better, ideally text documents over 10,000 words. For lines of text fewer than 50 words LIWC encourages a high degree of scepticism when interpreting the results, which obviously presents a problem for tweets. Interpreting aggregated sentiment of 10's of 1000's of tweets is one option (see our **detailed report**).

Options Dictionary Help

Source (A)	WC	Analytic	Clout	Authentic	Tone	WPS	Sixltr	Dic	function	pronoun	ppron	i	we	y
up by this man, please ~please~ use your vote wisely https://t.co/uuefukpJG2	26	32.33	98.93	5.76	99.00	26.00	15.38	76.92	46.15	23.08	11.54	0.00	0.00	7
#moors #trees #webstagram #prints... https://t.co/CPJWfUgRAf	18	92.84	50.00	4.97	25.77	18.00	27.78	27.78	11.11	0.00	0.00	0.00	0.00	0
o pod qué no lo voy a haced io" https://t.co/OXquLtrEER	25	88.07	21.18	1.00	91.14	12.50	16.00	20.00	12.00	0.00	0.00	0.00	0.00	0
	2	92.84	50.00	1.00	25.77	2.00	50.00	50.00	0.00	0.00	0.00	0.00	0.00	0
hed 2nd	12	6.55	50.00	1.00	25.77	12.00	33.33	66.67	41.67	25.00	8.33	8.33	0.00	0
lly or start a league with format restrictions. These have helped friends	23	80.03	66.81	27.39	25.77	11.50	26.09	82.61	43.48	4.35	0.00	0.00	0.00	0
istol) https://t.co/57YiNMpT9M #IT #Job #Jobs #Hiring #CareerArc	18	85.72	50.00	1.00	25.77	18.00	44.44	61.11	5.56	5.56	0.00	0.00	0.00	0
ooks #tshirts #retrogaming #retrotees #marvel #xmen #thundercats #doctorwho	19	76.19	85.38	1.00	97.58	19.00	42.11	47.37	15.79	10.53	5.26	0.00	5.26	0
	25	92.84	50.00	43.37	91.14	25.00	16.00	44.00	16.00	0.00	0.00	0.00	0.00	0
	11	3.76	96.52	1.00	25.77	11.00	9.09	100.00	54.55	18.18	9.09	0.00	0.00	0
to be layering 5 school jumpers on Emma Fackrell at once.	22	68.79	50.00	96.40	1.00	22.00	22.73	72.73	40.91	4.55	4.55	4.55	0.00	0
	4	37.39	1.00	74.76	25.77	4.00	25.00	75.00	25.00	25.00	25.00	25.00	0.00	0
for a minute and DM contact details? Thanks. Rich/South London Press.	25	88.07	94.50	1.59	99.00	6.25	12.00	88.00	36.00	4.00	4.00	0.00	0.00	4
is splitting. and for what reasons people give.	17	26.21	72.17	28.81	98.87	8.50	29.41	82.35	47.06	11.76	0.00	0.00	0.00	0
ng 500 #bees as a conservation research programme https://t.co/Elrtgqiwlv	22	87.28	50.00	1.00	1.00	11.00	31.82	50.00	22.73	0.00	0.00	0.00	0.00	0
o really care. Don't hide behind unjust power @GeorgeSteel2 @DickGraceless	21	17.96	50.00	68.01	95.81	7.00	19.05	76.19	52.38	23.81	9.52	4.76	0.00	0
: Art@Arlington, find out more: https://t.co/juKs1NUx7Z https://t.co/Cx19Gm495h	26	99.00	50.00	38.39	25.77	26.00	15.38	42.31	15.38	0.00	0.00	0.00	0.00	0
. #thowbacktime #summer2016... https://t.co/a8K3TKgKyT	18	60.80	95.20	23.51	99.00	9.00	33.33	72.22	27.78	5.56	5.56	0.00	5.56	0
see is rubbish most prob haha?? x	19	63.17	94.27	4.05	99.00	6.33	15.79	68.42	26.32	15.79	10.53	0.00	5.26	5
metal, wood and chemicals. It's the idiots behind them that makes them dangerous	19	33.88	70.08	1.00	1.00	9.50	26.32	63.16	42.11	21.05	10.53	0.00	0.00	0

Fig. LIWC dictionary output

What we found

Our big-data trial presented unchartered territory for us and unsurprisingly, we experienced a steep learning curve. Through this process we accumulated a wealth of learning that we hope can inform other frontline organisations considering this method of wellbeing data-collection. The main advantages and disadvantages of collecting big data in this way are outlined below.

Advantages and disadvantages of collecting and analysing Twitter data

Advantages

- **Lots of data fast:** Once you have your Twitter stream up and running you can accumulate a huge amount of data very quickly. In fact, there are no other wellbeing data collection methods that rival big data in terms of sample size. You would not be able to gather this much data using a wellbeing survey that relies on people engaging with, and taking time to fill out a questionnaire (at least not as fast).

- **It's a good listener:** Twitter streaming is a passive measure of wellbeing that has no direct influence on what people do or say- tweets are readily accessible in the public domain. Unlike surveys that 'ask', twitter applications 'listen'. Eliminating the extractive process of 'asking' that might bias people's evaluations (such as social desirability bias) can increase the validity of wellbeing data (Curti et al, 2015). In addition, once the application is set up the cost to simply run the twitter stream and collect tweets is relatively low and resource light.

- **It's 'trendy':** Although Twitter might be considered 'old news' by many people using the most current social-media apps, a lot of us are familiar with twitter and find social media 'interesting'. We can do and experience things on social media that can't be done anywhere else. We make our private thoughts instantly public, potentially on a global scale- a psychological experience never encountered before. This unique platform encourages disinhibition, meaning we say and do a lot of things we would not normally do in real life! Therefore, twitter data offers a source of very personal information that would not be expressed outside of the social-media sphere. For many, this is a much more interesting data-set than wellbeing survey-data.

- **Real-time data**: If everyone tweeted one tweet every day, this would give an amazing insight into how people are feeling and functioning in their everyday lives. It would be extremely unusual and incredibly difficult to get a real-time wellbeing update from a given population using any other method of data collection.

- **Sentiment analysis is speedier than you think:** Although the algorithms that make up a sentiment analysis dictionary are very complex, loading tweets in is quite straightforward. This is makes analysis of large amounts of data pretty efficient.

- **Data visualisation impact:** If you have the expertise and resources, there are lots of really interesting and exciting ways to visualise twitter data. Many people have used twitter streams to map tweets geographically showing what people are talking about in real-time. Data-visualisation is gaining increasing interest in many sectors as a powerful alternative to graphs for communicating lots of information. Twitter data is ideal for this because of how dynamic it can be, the quantity and geographical spread of it.

Disadvantages

- **Time and expertise:** If you do not have expertise within your organisation, getting up to speed with computer programming can take a very long time. Equally, if you are paying someone to create an application for you this can be very expensive. If you are richer in time than money, having a go at creating an application is not impossible but be prepared for a steep learning curve.

- **Quantity over quality:** Although you can gather large amounts of data, the quality and depth of the data can vary wildly from tweet to tweet. If you are using sentiment-analysis like we did, it can offer breadth of information about how generally happy/unhappy different regions are, but is limited in offering an explanation as to why. Although sentiment analysis dictionaries analyse personal text data, the meaning of any individual tweet is a drop in the social-media ocean. Like quantitative survey data, analysis outputs are expressed in numerical/statistical form and only become meaningful on a large scale. In addition, when you use sentiment analysis, the data is still expressed statistically- so even though tweets are qualitative data in themselves they are coded numerically into quantitative data- hence the the breadth versus depth trade off.

- **Internet connection:** Although data is collected passively, you still need to activate the stream which requires your computer to be turned on (potentially for hours) a good internet connection. For example, streaming tweets from the Bristol area for 1 hour 20 minutes collects around 1500 tweets. There are 'time-out' functions you can build into your code that turn off the stream after a certain amount of time, or when you have collected a certain amount of tweets which will differ depending on your resources. However, an unstable internet connection can terminate the twitter stream.

- **Source code maintenance:** Twitter's API (Application Programming Interface) does change which may mean you need to alter the source code you are using. You may also need to update the software that handles the twitter application.

- **Even small changes in the code can be difficult:** Occasionally your program will throw up errors- most of which probably make little to no sense. It's worth entering your error into search engines just to see if there's anything obvious you're missing, especially if the program was working fine a few minutes ago. Be aware that if tinkering with your code; either because you would like it to do something differently or because something isn't working, this can have big implications for the program. Save as many versions of your code as you can, because remembering what you delete or make changes to is tricky. If using Python, you can avoid deletions by commenting out changes with a '#'.

- **How good is your dictionary?** If using a sentiment analysis dictionary to analyse tweets, effective sentiment analysis will require a robust sentiment language dictionary. We invested in a LIWC dictionary which has proven to be successful at organising psychologically relevant content into meaningful categories. Not all sentiment dictionaries have shown to be as consistent or sensitive. Dictionaries often disagree and open-source options can vary in quality.

3.5 Wellbeing Wearables

As an alternative to asking people directly about their wellbeing, more and more people are experimenting with mobile, non-invasive data-collection methods that automatically detect and record our physical and physiological activity. This generally involves wearing biosensor technology somewhere on our bodies; fingers, wrists, clothes and heads!

Why wear them?

Research conducted by *MindShare* in 2015 identified 6 'need states' that wearable technology can satisfy:

1. **Flow**- making our lives easier, syncing with our lifestyles and patterns
2. **Reflection**- learning more about ourselves from the data we generate
3. **Affinity**- sharing and connecting personal experiences with family, friends or online communities
4. **Performance**- supporting us with certain tasks to improve our performance to achieve certain goals
5. **Value exchange**- tracking or data-sharing can be allowed for consumer benefit with the opportunity to exploit commercial value
6. **Self-expression**- people may feel good wearing and using wearables as a fashion item

What do they measure?

1. **Heart-rate variability (HRV):** is the measure of the natural variability of our heart rate i.e. how it goes up and down. Using an oximeter built into a ring, you can capture the unique patterns of heart beats in response to different emotional and cognitive states.
2. **Muscle activity**- can be measured using an electromyographic sensor built into special clothing
3. **Stress-** measured with an electrodermal sensor incorporated into a wristband.

4. **Physical activity or sleep patterns**- via an accelerometer in a watch
5. **Female levels of fertility-** Most 'fertile' time can be identified with body-tracking.
6. **Mental attention and brain activity**- monitored by a small number of EEG electrodes
7. **Vibration**- special clothing sensors can pick up vibrations that signal changes in emotional state

'Objective' wellbeing

In the future, measuring 'objective correlates' of wellbeing, or biological markers of 'wellbeing' could have increasing clinical applications for mental health management. Physiological activity (e.g. heart rate) and physical activity (e.g. walking distance) can be used to better understand people's self-reported feelings and emotions (i.e. subjective wellbeing) using a combination of the above measures.

For example, a number of parameters of heart-rate variability (HRV) decrease during anger. HRV indicates how well we can switch between our sympathetic ('fight-or-flight') and parasympathetic ('rest and digest') nervous systems i.e. high levels of HRV show how well we are able to adapt to changes in our environment. This data can then be understood in the context of other lifestyle information such as social events or self-reported wellbeing. When wearables are used alongside other data-collection methods we can explore patterns of how behavioural, psychological and physiological factors affect each other, their relationship over time and in different contexts.

Bio-feedback

Mobile wearables can provide biofeedback for managing stress, anxiety and health-related issues. Many offer personalised, immediate and goal-oriented feedback based on specific tracking data. This can be provided on a mobile phone that accompanies a wearable or on the wearable device itself.

Detected stress levels may be presented in a graph over time. You may also be able to compare stress levels with sleep and other data to provide a comprehensive picture of your physiological and physical activity.

A huge advantage of apps and wearables is their ability to translate quantitative data into personalised qualitative data when giving us feedback: providing meaningful descriptions of the numbers.

Benefits and advantages of wearable technology
➢ **Can be empowering** for individuals to gain self-knowledge using the feedback generated by their personal tracking data. They may make more informed decisions and prevent life-style related problems. ➢ **Data-visualisation:** Many wearables with their corresponding applications automatically visualise your data. This makes the process from data-collection to analysis to reporting, very efficient. ➢ **Granularity**- can provide amazing detail of information about an individual and multiple datasets can be incorporated to provide a rich picture of a person's lifestyle, activity and wellbeing.

- **Long-lasting-** most wearables provide long-lasting functionality and require little charging.

- **Practical-** for many people wearables (e.g. those you can wear on your wrist) offer an advantage over mobile phones due to their constant availability.

- **The 'Internet of Things'-** The use of biosensors provides exciting opportunities for interconnection of digital data sets ('Internet of Things'). If 'individual big data' can link up with other digital sensors in living spaces or transport and energy data, this could provide an incredibly rich 'living map' of information which could inform decision making: maximising the functionality of urban systems.

- **Relieving the burden-** Enabled synchronisation of data from wearables eases the workload of manually tracking and recording. Data is generally in an accessible and appropriate format to analyse.

- **Experience enhancing-** Some innovative wearables are focused on using biofeedback to enhance positive experiences or improve communication e.g. vibration sensors that pick up silent emotional states which can be tagged on to our digital messages to overcome interpersonal barriers of texting.

- **Gamification and social sharing-** Wearables can provide 'gaming' elements which are useful for engaging people with their health and wellness data. For some people, competitions and sharing of data socially in virtual worlds can be both rewarding and motivational.

Barriers and disadvantages of wearable technology

- **Limited evidence of effectiveness-** as with mobile apps there is little research showing the effectiveness of wearables for improving health and wellbeing.

- **Validity-** the process of validating wearables (i.e. checking they are measuring what they say they are measuring) is essential. 'Objective correlates' of subjective wellbeing are inherently difficult to verify and often need to go through extensive piloting. Some sensors may not be sensitive enough or may themselves affect people's biological responses. You might be able to buy a wellbeing-monitoring wearable online, but is there evidence to say it actually measures wellbeing?

- **Difficult to anonymise-** De-identifying wearable data can be very difficult due to its user-centric nature. This is a data protection problem if passed on to third parties, as it is possible to identify people by their 'digital trace'

- **The novelty factor**- Research suggests 32% of wearable users stop wearing them after 6 months. There is often a novelty associated with health data, which means wearable tech cannot continue to inform behavioural change long-term and data is not collected over long periods of time.

- **Error rate**- A large number of wearables marketed for tracking physical activity for example, show huge variations in accuracy with error margins up to 25%.

- **Data ownership**- Similar to mobile apps, there is controversy over who 'owns' data collected by wearables. Generally, wearable manufacturers own the data, and can also pass it on to third parties.

- **Over-reliance**- Wearables may give users a false sense of security regarding their health, or encourage obsessive self-monitoring.

- **Uncomfortable and intrusive**- Many users find wearables to be cumbersome and an interference in day to day living.

- **Not for everyone-** The relationship between a user and wearable device is complicated, and our personality is likely to play a key role in 'perceived usefulness'. The majority of people using wellness apps and wearables are people living healthy lifestyles who want to quantify their progress- this shows how wearables may appeal to a specific demographic.

- **Could be more accessible-** Research suggests the majority of people making use of their quantitative-self data are professionals, software engineers and data scientists with the skills and knowledge to analyse it. Technical data is useless for people who don't feel equipped to make sense of it.

- **Where's the rest of it?** Many wearables and their corresponding apps only report a tiny amount of the data they collect. Considering the large amount of data wearables can collect, providing trivial amounts of data can feel a bit of a waste. In addition, many manufacturers charge money to get your full dataset.

- **Cost**- If you are looking to invest in wearables for your staff members to assess wellbeing, this can be a pricey alternative to a wellbeing survey!

3.6 Using apps to collect data

'Happy Bristol' app

Alongside the *Happiness Pulse* pilot, Happy City worked in partnership with the Happiness Research Organisation in 2016 to develop the 'Happy Bristol' app. As well as gathering valuable data about the happiness of people in Bristol, we wanted to explore the feasibility of creating a mobile app and the opportunities for wellbeing data-collection.

We worked in partnership with the Happiness Research Organisation (HRO) to develop the app using their existing 'Happiness Analyser' framework. The app was tailored so questions were asked specifically about Bristol. The HRO agreed to develop the app and analyse the data pro-bono as this presented an opportunity for them to collect valuable information about the happiness of people in Bristol.

To understand the importance of location and wellbeing we made it possible to link up data from the Happiness Pulse and the 'Happy Bristol' app using respondents postcodes. For those that completed both, the two datasets offered a rich combined dataset.

'Happy Bristol' app and the Happiness Pulse

The 'Happy Bristol' app was listed on the Happiness Pulse website in our 'Explore More' pages, as a resource for those who wanted to continue exploring their wellbeing using a daily measurement tool. Our primary aim was to explore whether those people who took the Happiness Pulse wellbeing survey would be interested enough in their wellbeing to explore their wellbeing on a day-to-day basis via an app- the Happy Bristol app. The app was available to download on Android and Iphone via our website, or users could complete the online version.

What we found

The app was officially available on our site from 21/06/2016 until late August. We had relatively low uptake of the app, and as such the app did not yield any statistically relevant data for Bristol citizens. Few downloads may have been partly due to technical issues on the webpage; this delayed its release date which meant it did not receive the beneficial press coverage and communications drive for the Happiness Pulse.

In future, it is very likely that having the app more visible on our site for longer at key web traffic times would increase the profile and uptake of the app to gather more meaningful data. Alternatively we could speculate that low uptake reflected low-interest in downloading a wellbeing app, but this is difficult to ascertain before we further investigate the Happiness Pulse website data. We expect to share our full report for the Happiness Pulse in October 2016, see our website **here** to keep up to date with Happy City projects and publications.

We have learned a great deal about the feasibility of using online surveys, mobile and Twitter applications to collect wellbeing data which has informed our quantitative and qualitative guides for wellbeing data-collection.

How useful are apps for wellbeing data collection?

Advantages	Disadvantages
➢ **Machine learning-** the algorithms used by mobile apps provide huge opportunities for analysing data in ways that would be impossible manually. Technology can learn as more data is inputted, detecting patterns and categorising information based on complex calculations. ➢ **Accessibility-** anyone with a phone, tablet or laptop can monitor and explore their personal wellbeing. Mobile phones can also make use of wireless internet which is useful for those who don't have access to a computer. ➢ **Multi-lingual-** drop down lists for different languages can be incorporated into mobile applications: offering an obvious advantage over paper questionnaires.	➢ **Under-regulated**- Often little is known about the quality of mobile apps beyond user star-ratings. See **below** for more discussion on the legislation surrounding mHealth applications. ➢ **Data fabrication-** Mobile/online surveys can still be subject to inaccurate and unreliable data. ➢ **Less control-** If you are creating an open survey or downloadable app, your sample will be self-selecting as your method of recruitment is indirect. This may bias your results if your sample is unrepresentative. ➢ **Cost-** Although there are some free or low cost mobile-survey alternatives, many mobile app-developers price on a per-survey basis. More sophisticated apps with complex functions are obviously going to cost more to build. ➢ **Where's your phone?** Passive measures are dependent on

- **Offline**- Many apps can collect and analyse data offline.

- **Complexity and depth of analysis-** smart phone apps can provide an incredible amount of user-specific data. Complex, multiple data sets can be collected and combined to create 'individual big data', making links between wellbeing and unique behavioural patterns.

- **Breadth**- because the data is quantitative, it can also be meaningfully compared to other data sets and can be very powerful on a larger scale for example, to analyse the relationship between geographical location and wellbeing.

- **Reliable data-** if data is automatically uploaded, analysed and reported on this reduces the risk of human error and data-loss, increasing reliability.

people having their phone with them to record data.

- **Culture**- there is much variation in how people use mobile devices.

- **Depth**- Mobile apps/surveys are best placed to capture quantitative data, as machine algorithms are not really equipped to carry out qualitative analysis techniques. Like other forms of quantitative data, data lacks depth of detail about individuals' experiences.

- **Impact on wellbeing**- As many mobile apps have not been clinically tested, the impact of completing daily questionnaires, constant notifications, and receiving 'feedback' is not fully known. Some apps aiming to collect wellbeing data may actually have a negative impact on wellbeing which has consequences for the individual and the reliability of data collected.

3.7 Digital wellbeing data: conclusions

Good quality data collection from wellness wearables and their corresponding apps relies on users being engaged with the technology and the process. There are a number of techniques that can encourage user-engagement of digital tools.

1. **Gamification**- adding a 'gaming' aspect to the tool. This can be in the form of competitions and challenges incorporating visible feedback. This relies on principles of social influence or rewards that can be reinforcing.
2. **Ambient feedback**- subtle or unintrusive visual feedback of data that doesn't require conscious attention, e.g. *UbiFit* for example, uses a garden metaphor to present activity data- more flowers and features in the garden symbolise increase in physical activity
3. **Contextualising-** Information from wearables that generate smart interventions have the potential to encourage positive behaviour change. Context-aware algorithms can identify what the user is doing from sensor data, motivational prompts can then be given at specific, influential times. Some wearables can also tell when the user needs support.
4. **Adaptability-** Studies have shown people prefer to personalise the user-interfaces of apps and wearables. Future devices need to be able to support our lifestyles and be more equipped to adapt to user's preferences. If people don't need to adapt their behaviours to much to 'make space' for a wearable or app this could lead to longer-term retention.

The general feeling is that more needs to be done to ensure use of wearables in the long-term to collect and use wellbeing data. Incorporating wearables more seamlessly into our everyday lives on our own terms will ensure users remain engaged with this technology.

The future of digital wellbeing

The way we view and use our personal data is constantly changing, and wellbeing apps and wearable technology will continue to adapt to meet our changing needs as consumers. It is likely that the quality and testing of apps will increase, as well as our reliance on data collected by digital devices.

- **Better regulation**- Currently, evidence of the clinical applications of wearables and mobile apps is limited at best. Many who market devices underestimate the jump from designing a product seemingly related to health and wellness, and actually providing evidence to support these fundamental assumptions. For consumers, accuracy of data appears to be a primary concern, which increases pressure on manufacturers to reduce error rates and improve the quality of the technology they are selling.

   - *Apple* are currently leading the way in developing an open source software framework which could accelerate and standardise procedures for regulating *Apple*'s apps. If other manufacturers follow suit, this could lead to a robust regulatory framework that encourages large scale randomised controlled trials to make wearables safer and more effective.

- **Patient-empowerment**- Experts predict the popularity of health and wellbeing apps and wearables will continue to increase. We should expect more people to bring along their digital measurement tools on visits to health practitioners. Whereas this may be empowering, it may also bring increased anxiety for both patients and practitioners.

- **The Internet of Things-** The internet of things (IoT) is the network of physical devices, vehicles, buildings and other items that collect and exchange data. Connecting up different streams of data that collect useful information e.g. via sensors, software and capitalising on the interconnectivity of systems can be incredibly insightful for cities. For example, we can potentially make links between traffic systems, weather reports and even wellbeing data. It is predicted there will be over 20 billion objects or devices connected in the IoT by 2020, which includes mobile devices.

4.0 Closing remarks

Quantitative data is useful for gathering breadth of information about wellbeing, whether it be a one-time survey or an evaluation of a specific wellbeing intervention. Statistical or numerical data can be easy to analyse and powerful when visualised. Digital forms of quantitative data collection such as big data and mobile apps present new opportunities and challenges for collecting different kinds of wellbeing data with technology. There is no 'one size fits all' approach and the range of quantitative methods of data collection discussed in this guide offer benefits and limitations. Your method for data collection should be dictated by your needs as an organisation, research questions and resources. Again, it is advisable to collect both qualitative and quantitative data to gather both breadth and depth of information (see our qualitative guide **here).**

This guide is not intended to be comprehensive but provide some basic information about good practice when collecting quantitative wellbeing data. The list of useful links are included as signposts to other resources which can hopefully provide further detail in your specific areas of interest.

If you have already collected wellbeing data and want to evaluate the wider impact and value of a wellbeing intervention in key policy areas, please see our digital measurement tool- the **WellWorth policy toolkit**. (**link**)

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