

1 **1. Do biomedical data have special significance?**

2 Biomedical data that reference individuals are, and have always been, a special class  
3 of data subject, in general, to restricted access. When biomedical data consisted  
4 primarily of patient records in GP's offices and hospitals, and were mostly paper  
5 based, managing such data was as easy as controlling physical access to the files. With  
6 digitisation making biomedical data accessible (in principle) to anyone with an  
7 internet connection, and with the advent of large molecular datasets the ethical  
8 concerns have changed in that there is now a much higher likelihood that such data  
9 may be accessed by someone without the proper permissions. Furthermore, it is  
10 clear that 'omics data, are more useful when aggregated so health care providers are  
11 keen to collect large data sets for population-level analyses.

12 Such analyses, used for instance to identify disease-causing genetic differences,  
13 genetic differences that affect drug metabolism, and changes in the genomes of  
14 cancer cells, have led to improved prevention, treatment, and diagnosis for many  
15 patients. Such benefits are likely to increase steadily as more data from more  
16 individuals is aggregated and studied, and this is a real revolution in medical  
17 treatment.

18 Genomic information is often classified as being special because it is unique – i.e.,  
19 the data contain enough information to specifically identify a person. This does not  
20 mean it is a straightforward task to take this information and then identify a specific  
21 person in the population from it. This distinguishes it from information that is  
22 potentially less unique but easier to use for identification (e.g. post codes). The  
23 uniqueness of genomic data is a feature shared with other (potentially as  
24 widespread) datasets, such as RNA or protein levels; these are often grouped  
25 together as 'omics data.

26 The real feature of genomes (as well as transcriptomes, proteomes, etc.) is that their  
27 information content is unique to a single individual. This characteristic is shared by  
28 traditional single dimensional biometric data types, such as fingerprints and iris  
29 scans, but is also shared by other non-biometric multidimensional, and indeed  
30 mundane, aspects of human behaviour such as typing and driving speed patterns.

31 The combination of such datasets associated with each individual is likely to increase,  
32 and to become unique, in particular if the datasets are rich enough to be interesting  
33 also for health care research. We believe that over time the “special position” of  
34 genomic information will progressively merge with the more general problem of  
35 providing access to all types of information that uniquely identify an individual. The  
36 ethical framework is likely to require a switch from trying to guarantee that the  
37 information does not uniquely identify a particular individual towards preventing  
38 inappropriate use of information by researchers, or to inadvertent use.

39 With respect to genomics it is clear that family members may share an interest in the  
40 findings for a particular individual, but other less unique types of information such as

41 postcodes and religion, albeit with less certainty of transmission, also share this  
42 characteristic. The clinical genetics community has already had to navigate complex  
43 between-family-member scenarios for the release of information, and also the  
44 discovery and informing of unexpected findings, e.g., of misattributed parentage. It  
45 is worth using the long experience of this community to help structure how the  
46 release and use of information is propagated amongst family members.

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## 2. What are the new privacy issues?

49 Biological “big data” like traditional paper-based medical records, may contain  
50 private information that patients do not wish made public, and that medical systems  
51 by custom keep private. “Big data” are different in that, by definition, they are held  
52 in a computational infrastructure and are therefore more accessible, and in the scale  
53 of information – including both constant lifestyle measurements as well as unique  
54 information such as the genome.

55 Big biological data can be separated in two types: molecular data such as genomes,  
56 transcriptomes, etc. which are unique to an individual, but which are difficult to  
57 analyse and therefore unlikely to be used for identification even if inadvertently  
58 released, and lifestyle and personal phenotype information that might be less  
59 unique but carry more risks if inadvertently released. We would advocate an  
60 approach that balances the risks of harm on identification with the benefits to  
61 society for the aggregated research.

62 The risk of harm has three components; the first is the protections (both  
63 technological and practice based) to prevent malicious use (eg, by signing  
64 agreements on research use) and minimising the likelihood of inadvertent release.  
65 The second is the ability to change a unique piece of information (genomic,  
66 transcriptomic, lifestyle, or another measurement) to identify an individual. The  
67 third is the harm which an individual would suffer if information can be assigned  
68 back to that specific individual. The benefits are society-wide in terms of better  
69 health care practice, better discovery for biomedicine and potentially lower costs in  
70 the health care system. Currently most focus has been on the first of the risks, and  
71 not the second two, and the case for benefits is often implicitly and not well argued.  
72 We believe there should be a more systematic and broader outreach about the  
73 benefits of more accessible data, while acknowledging and minimizing, but not  
74 eliminating, the risks of harm.

75 We note that the value of aggregate data is not changed if the data (e.g. a genome)  
76 from one or a few people are not included. Thus, provided that most individuals do  
77 consent to release of their data, which seems likely, the reluctance of a small  
78 percentage of the population to release their data will not affect research outcomes.  
79 Given the often widespread uptake of cohort studies in the UK (eg, BioBank,  
80 GoSHARE, NIHR BioResource) this means that an active consent process is likely to  
81 accrue most of the benefits.

82 Since most individuals do not have backgrounds in biological science it seems likely  
83 that most individual’s data will be used in ways that they are unaware of. This should  
84 be noted when consenting the data. In some ways this is already true of traditional  
85 medical records, where reporting of (de-identified) infectious disease cases is  
86 required by law in some jurisdictions, and where overall counts for numerous  
87 diseases are routinely collected for large areas and even entire countries.

88 Social networking and the sharing of information have become the norm for most  
89 people, and certainly for younger people. It seems likely that individuals who actively  
90 participate in social networks will be accustomed to the notion sharing data and will  
91 be less concerned by the aggregation of data for society-wide health care benefits  
92 (as they are comfortable for aggregation of data for commercial gain by companies  
93 providing “free” services to enable this aggregation, e.g., Facebook).

94 As we note above, biomedical data are functionally equivalent to the data in  
95 traditional medical records, which are treated as private information but not as  
96 property. It would seem sensible to continue treating newer data types the same  
97 way. If these data are deemed to be “property” we suspect that distribution for  
98 research and public health uses will be curtailed, or made more difficult, while  
99 having little additional value for the individual.

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### 3. What is the impact of developments in data science and information technology?

New technologies for DNA sequencing, transcriptomics, proteomics, metabolomics, and other 'omics' methods have fundamentally changed the boundaries of what is possible for biomedical researchers. These technologies generate vast quantities of data that have enabled large-scale big picture experiments that look at, for instance, the genomic variation in whole populations, or the genetic and metabolomic structure of the gut microbiome over time. These technologies also allow very fine-scale experiments to examine ever-finer aspects of cellular and organismal biology, for example how gene expression or metabolic processes change over time or in response to specific environmental stimuli.

In response to these new technologies scientists are now designing experiments with broader reaching goals aimed at understanding more complex questions and funding agencies have responded with programmes that implicitly assume the use of "big data" projects. For example, the 2011-2015 BBSRC delivery plan explicitly lists data intensive science as a priority, and the other grand challenges: food security, industrial biotechnology, and fundamental bioscience to improve wellbeing; all assume the use of data intensive technologies to address these challenges.

Should "big data" be defined? This is difficult. For a single scientist the output of a single run on a next generation sequencing machine is "big data" since storage and analysis of this single dataset might exceed the physical capacity of the his or her lab's computational infrastructure and the lab may not have anyone with the expertise to deal with the data. At the other end of the spectrum, for large organisations such "big data" is much bigger and is measured in petabytes of disk, or in the output of thousands of next generational sequencing runs. For the single researcher or a large organisation data become "big" when they approach or exceed storage and analysis capacity.

The experience shared by single researchers, large organisations, and everyone in between is that at every scale our ability to generate data is growing faster than our ability to manage, store, and analyse those data. This, perhaps, is how "big data" should be defined: not as a quantity, but as a rate.

Among biomedical scientists this growth problem is a well known and well discussed problem. There are numerous large-scale initiatives to address the problem. Within Europe the ELIXIR research infrastructure is developing a large distributed infrastructure to store and analyse big biomedical datasets and, importantly, also includes numerous initiatives for training researchers (and clinicians) to understand and analyse big data. Other European initiatives include EUDAT, specifically aimed at dealing with the "long tail" of data that are not addressed by the larger infrastructures, as well as the Research Data Alliance, which is a worldwide effort to coordinate storage and analysis of large data.



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**4. What are the opportunities for, and the impacts of, use of linked biomedical data in research?**

144 The opportunities for linked data are enormous. From a public health and medical  
145 perspective big data presents opportunities in personalised medicine (genotype-  
146 based drug dosing); cancer diagnosis and treatment; and epidemiology (identifying  
147 and tracing infectious disease, data mining health records). There are a number of  
148 major challenges to real advances in this area. It is important to regularly restate the  
149 fundamental benefits of analysing large scale cohorts in discovery in biomedicine;  
150 without this analysis much of the health care that we have today would not be in  
151 place, and if we do not continue to enable and grow our ability to gather data we  
152 seriously jeopardise the chance of effective and efficient healthcare in the 21<sup>st</sup>  
153 century.

154 Commercial firms have played an important role in many aspects of biomedicine  
155 from the development of drugs to devices. Much of this development requires  
156 appropriate safety measures which often require large patient populations (clinical  
157 trials). Therefore many commercial firms by definition do large scale, “big data”  
158 cohort research now as part of their operations. This is likely to increase in the future.

159 When use of and access to cohorts is driven by a biomedical endpoint, there is little  
160 to distinguish commercial and academic research. However, there should be  
161 appropriate controls that commercial companies do not reposition the data outside  
162 of the biomedical context (for example, allowing the data to be combined with other  
163 information about individuals for targeted marketing).

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**5. What are the opportunities for, and the impacts of, data linking in medical practice?**

167 Again, the fundamental benefits of cohort based research need to be regularly  
168 restated. Patient cohort based research is a key part of many of the medical  
169 innovations currently used (not least the clinical trials of successful drugs) which has  
170 both extended life and improved quality of life for the entire population. In the  
171 coming century we will need to deepen our understanding of disease aetiology and  
172 treatment, with proactive screening, better diagnosis, better treatment and better  
173 on-going care. To do this effectively and efficiently we need to have large scale,  
174 information rich cohorts with both lifestyle, physiological and molecular readouts. A  
175 key concern we have is that the risk of harm to individuals is overstated whilst the  
176 benefits to individuals as part of society is understated.

177 In a number of health care scenarios there is already appropriate sharing of  
178 information between the health care system and other services; for example in the  
179 integration of health, social services and educational information for children.  
180 Already a number of cohorts have the ability to link beyond just healthcare data,  
181 such as the SHIP system in Scotland. We note that this further linkage includes less  
182 unique information that may nevertheless be easier to use for identification and  
183 therefore there may incur a higher risk of harm. However, biomedical studies in a  
184 number of areas (for example, dyslexia or extreme behavioural disorders) by  
185 definition will cross these boundaries. With appropriate controls to minimize risk,  
186 this linkage seems appropriate.

187 The use of this information for identifying “high risk” individuals is effectively a  
188 screening procedure. There is extensive research and experience on how to assess  
189 and model effective screening for public health, which requires a careful analysis of  
190 both the benefits and harms (for example, even a low false positive rate can mean a  
191 well meaning screening program does not have population level benefits). Any use  
192 of information as a screening mechanism should be rigorously assessed, and only put  
193 into place after such an assessment.

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**6. What are the opportunities for, and the impacts of, using biomedical data outside biomedical research and health care?**

197 There are two levels of wider use of biomedical data. The first is the use of  
198 biomedical data with respect to associated components of the public services, such  
199 as social services and education. Where it is in the public benefit there should not be  
200 a strong boundary between “biomedical data” and “other social data”, though  
201 noting again that other social data might be less unique but carry more risks on  
202 inadvertent release.

203 A special case is the use in forensics. As more biomolecular (in particular genomic)  
204 information is determined for health care usage it needs to be clear to all parties –  
205 patients, health care providers and forensic officers that there are limits to the use  
206 of health care data. We are unclear on the current status of health care data with  
207 respect to criminal or civil investigations; the presence of larger amounts of DNA will  
208 allow new potential forensic routes if desired. This needs to be examined and  
209 debated.

210 The second level is the use of this information outside of the public benefit, such as  
211 in commercial companies to help improve the profiling of individuals. This is  
212 inappropriate and not desired.

213 The question of predictive analytic tools for aspects such as recruitment is  
214 presumably something which interacts with discrimination of people by other means.  
215 This data should be seen in the light of discrimination policies and laws.

216 Once an individual’s data has been used in aggregate in analysis, it is effectively  
217 impossible to remove that information inherently from aggregate analysis.

218 As people routinely exchange personal information for access to other goods (in  
219 particular in social networking and many commercial offers) it seems impossible to  
220 ban individuals from profiting from their own data. However, we do not think that  
221 direct monetary profit is the best motivation for individuals to provide information  
222 for the public good, and the broad uptake of many cohorts stress this.

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