Making the most of Big Data in Plastic Surgery:

Improving Outcomes, Protecting Patients & Informing Service Providers

John A. G. Gibson[1,2*], Thomas D. Dobbs[1,2], Loukas Kouzaris[3], Arron Lacey[4], Simon Thompson[4], Ashley Akbari[4], Hayley A. Hutchings[3], William C Lineaweaver[5], Ronan Lyons[4], Iain S. Whitaker[1,2]

1. Reconstructive Surgery & Regenerative Medicine Research Group, Institute of Life Science, Swansea University Medical School, Swansea, UK.

2. The Welsh Centre for Burns and Plastic Surgery, Morriston Hospital, Swansea, UK

3. Swansea University Medical School, Swansea University, Swansea, UK

4. Health Data Research UK, Swansea University Medical School, Swansea University, Swansea, UK

5. JMS Burn and Reconstruction Center Merit Health Central Hospital Jackson, MS

Keywords

Plastic Surgery; Big Data; health care analytics; outcomes research; patient registry; patient database

Abstract

In medicine, “big data” refers to the interdisciplinary analysis of high volume, diverse clinical and lifestyle information on large patient populations. Recent advancements in data storage and electronic record keeping have enabled the expansion of research in this field. In the United Kingdom, Big data has been highlighted as one of the Government’s ‘8 Great Technologies’ and the Medical Research Council has invested over £100 million since 2012 in developing the Health Data Research UK infrastructure. The recent Royal College of Surgeons commission of the Future of Surgery concluded that analysis of big data is one of the four most likely avenues to bring some of the most innovative changes to surgical practice in the 21st Century.

In this article, we provide an overview of the nascent field of big data analytics in plastic and highlight how it has the potential to improve outcomes, increase safety and aid service planning.

We outline the current resources available, the emerging role of big data within the sub-specialties of burns, microsurgery, skin and breast cancer and how these data can be used. We critically review the limitations and considerations raised with big data, offer suggestions regarding database optimisation and suggest future directions for research in this exciting field.

Introduction

Although Big data has been highlighted as one of the UK government's '8 Great Technologies and it been a widely used term in the contemporary literature, it is often seen as a nebulas concept with several definitions(1). In healthcare it is commonly said to refer to the interdisciplinary analysis of high volume, complex and diverse clinical and lifestyle information. It encompasses a number of different data sources and analytical techniques that have not traditionally been seen or utilised in healthcare before. In 2011, David Cameron, the then Prime Minister, famously quoted that every patient was a "research patient"(2), paving the way for the use of data from all patients within a healthcare system to be used in big data analytics. The Medical Research Council (MRC) subsequently invested £120 million in health informatics(3) to drive this area of research forward.

We are now entering an era where access to big data and research emanating from it will be of immense benefit to practising plastic surgeons. The recent Royal College of Surgeons of England Commission on the Future of Surgery concluded that analysis of big data is one of the four most likely avenues to bring some of the most innovative changes to surgical practice(4). Other specialities are already taking advantage of significant research council investment and centralisation of resources within the United Kingdom (UK) to begin harnessing the potential of big data (Table 1). We will outline potential sources of data, as well as briefly discussing some analytical techniques and difficulties associated with this field of research. Most importantly, we aim to highlight areas of plastic surgery that could benefit from the field of big data research, inspiring all readers to push the boundaries of this exciting research field to improve patient care.

Table 1-Big Data in other medical specialities

Name	Aim	Data Sources	Analysis	Results
Dementia Platform UK(5)	A multi-million pound national collaboration funded by the Medical Research Council, aiming to improve knowledge on the pathogenesis of dementia.	Electronic Health Records, genetic samples and MRI images of a cohort of over 2 million participants.	Launched in 2017, numerous studies are currently in progress.	N/A
Deepmind and Moorfield's Eye Hospital(6)	To develop a diagnostic tool, that interprets Optical Coherence Tomography (OCT) images of the retina.	OCT images of the retina, provided by Moorfield's Hospital.	Artificial Intelligence. A deep classification network, trained with 14,884 images with known diagnosis, interprets the images.	No significant difference in error rate when compared to clinical specialists.
Deepmind Streams Application(7)	Real time analysis of blood results, alerting healthcare professionals of Acute Kidney Injury (AKI).	Blood results.	Blood results analysed according to pre-set algorithm. Warning of AKI, sent directly to the Deepmind Streams Application of clinical team caring for the patient.	
Breast Cancer(8)	To develop a tool that is able to interpret mammogram images.	Mammogram images obtained from the Digital Database for Screening Mammography, Florida.	Machine learning trained with supervision from clinical staff interpreting mammograms.	90% sensitivity.

What are big data?

Big data refers to datasets that have three defining key characteristics: volume, variety and velocity(1). More recently, other attributes have also been considered, including variability (consistency of data over time), veracity (trustworthiness of the data obtained) and value(9).

Volume refers to the volume of data per "transaction". The volume per transaction has grown exponentially from bytes (e.g. traditionally recording free flap observations every 6 hours), to kilobytes (e.g. clinic letters), to megabytes (e.g. clinical photographs), to gigabytes (e.g. Computed Tomography images), to terabytes (e.g genomic sequencing)(10). Consequenly, large volumes of data are being accumulated; in 2011 data from the United States of America healthcare system reached 150 exabytes (161061273600 gigabytes)(11), the equivalent of 9 billion copies of the James Bond collection on DVD.

The variety of data available makes health analytics both exciting and challenging (Table 2). Traditionally, the data collected and analysed has been structured. Structured data are data that can be easily stored, manipulated and analysed. Such data includes familiar input fields that are easily coded into traditional databases such as patient demographics, diagnostic codes and treatment reimbursement codes. However, over 80% of current healthcare data exists in an unstructured format such as hand-written clinical records and operation notes(12).

Furthermore, new data streams of both structured and unstructured data are becoming available, such as information from wearable devices (fitness devices, ECGs, glucose monitors), genetics and genomics, clinical trial data, social media feeds, geographical type data (person and service location) and smartphone applications. One component of big data is therefore built around how to manage, clean and analyse these new and unstructured data sources that are rich in content. This will be discussed later in this article.

Velocity refers to the speed at which data are collected and processed. Advanced analytic techniques, such as machine learning, offer the ability for real time data processing. Traditionally, healthcare data has been mostly static (data that does not change once it has been recorded e.g. clinical images such as a plain chest radiograph)(10), however more sources of data are available on dynamic variables e.g. vital signs. Real time accumulation and processing of dynamic data has significant advantages, particularly in the monitoring of a patients condition and the early identification of a change requiring intervention.

Table 2 Sources of data utilised in big data

Source	Description
Electronic Health Records (EHRs)	Patient records have become increasingly computerised in both primary and secondary care to facilitate communication and improve patient care.
Databases and Registries	A wide range of plastic surgery related international databases and registries exist, such as those for general plastic surgical procedures(13), oncology(14, 15), aesthetic surgery(16, 17), trauma and burns(18, 19).
Clinical Trial Data	The concept of "open data", whereby raw clinical trial datasets are made freely available to all, is becoming an increasingly encouraged and in some cases required for publication(20).
Social Media and Web Searches	A large percentage of patients and healthcare professionals use the Internet and social media, providing data for both research and clinical practice (21).
Wearables	The rise in wearable technology has the potential to provide vast and rich data(22). These data could help plastic surgeons in the monitoring of post-operative patients, collecting data on activity levels once discharged, or tracking patients around a hospital to improve workflow efficiency.
Genetics and biological data	The combined analysis of genomic, proteomic and clinical data has potential to provide further insights into tumour development and genetic profiling, paving the way for personalised medicine.

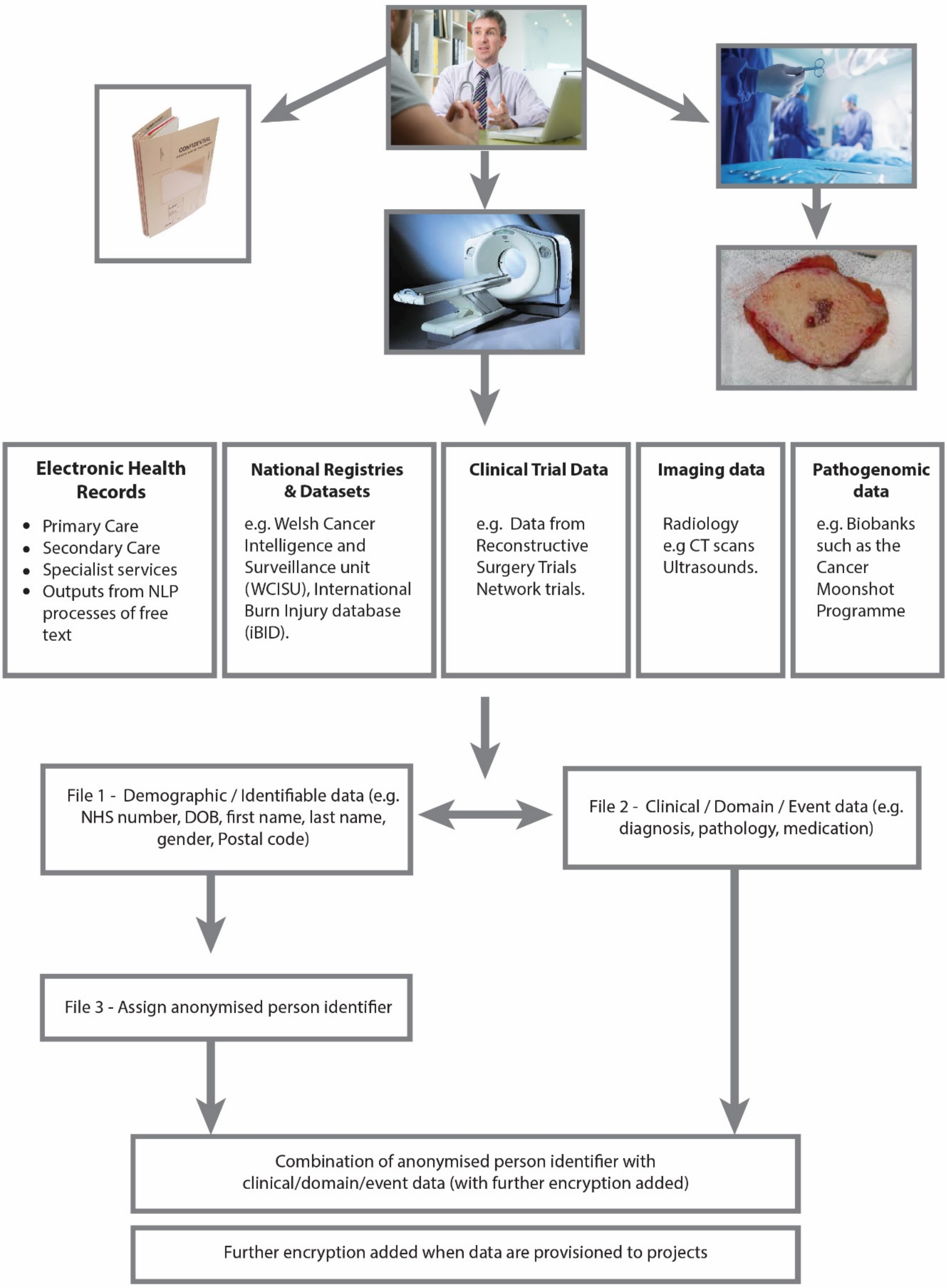
Management of Data

A practical challenge in big data research is the need to ensure that health related data are acquired, stored and analysed in a manner that is socially aware and appropriately governed. Problems with electronic capture of routine clinical data in the UK were demonstrated by the NHS National Programme for Information Technology (NP*f*IT). While the cause of this was multifactorial, the lack of collaboration between stakeholders were common themes(23).

The development of Data Safe Havens (DSH), in the early 1990s, has been crucial to ensure data is appropriately managed. DSH adhere to 12 principles, based on three themes. Firstly, data must be managed according to collection and storage of data that preserves confidentiality, adheres to ethical and legal requirements and allows appropriate, secure access. Secondly, the data must be accurate and reliable. Finally, the criteria relate to maintaining the security of data(24). Working to such standards allow DSHs to provide access to health data to enable research while protecting the confidentiality.

Examples of DSHs are seen in Australia(25), Canada(26), Scotland(27), England(28) and the Secure Anonymous Information Linkage System (SAIL) in Wales(29). The SAIL databank is a privacy protecting repository for population level person-based anonymised health and socio-economic administrative data, which provides a good example of how DSHs receive and manage data according to best practice(29-31). Figure 1 illustrates the overlying architecture of the SAIL databank system.

Figure 1 A diagram of how data enters the SAIL databank



Data Analysis

The analysis of big data requires an interdisciplinary collaboration between data scientists, researchers and clinicians in order to manage very large datasets, analyse them appropriately and present the data in an understandable manner(1, 10). Firstly, familiarisation and understanding of the data is essential to ensure relevant data are extracted. Data extraction is commonly performed using Structured Queried Language (SQL) to create data in a structured format suitable for analysis.

This extraction process is more complicated for unstructured data such as clinic letters or operation notes and is an area where Natural Language Processing (NLP) is beginning to play a role. NLP employs techniques from embedding expert knowledge into rule-based systems, to statistical learning methodologies such as Artificial Intelligence (AI) and Machine Learning (ML). While rules based systems require expert knowledge, AI and ML methods can use experts to annotate unstructured text with direct coding systems to train models and infer knowledge from new, unseen data (fully supervised ML)(32). Alternatively a data driven semi-supervised or unsupervised technique can be utilised to mine novel patterns from text that might not be considered by experts(33).

Once data are extracted they can be analysed either in a similar approach to traditional data or with new techniques from the field of artificial intelligence and machine learning (Figure 2).

Key definitions(4, 34)

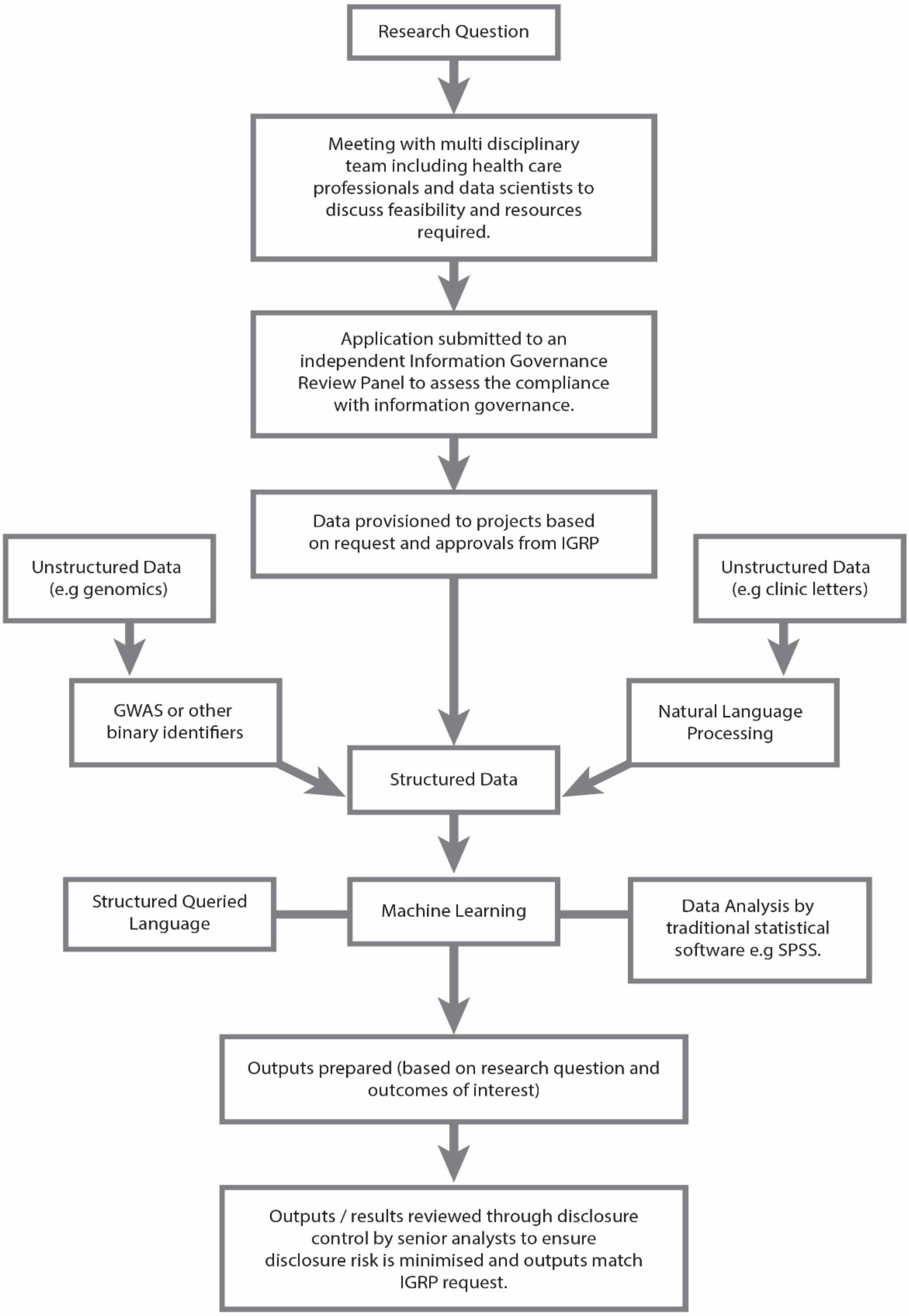
Artificial Intelligence - A field of computer science studying mechanisms that allow machines to perform tasks that would normally require human intelligence.

Machine Learning - A form of AI that enables machines to learn from data and patterns they analyse, rather than prior programming by experts i.e clinicians.

Natural Language Processing - An area of computer science in which computer programs are developed to ‘read’ and understand human written language.

Deep Learning - A type of machine learning inspired by the functioning of neural networks in the human brain. It uses algorithms to analyse different layers of data, establishing hierarchical relationships between the outputs of one layer and the analysis of the next. It thus enables learning through the recognition of patterns and the interpretation of data and images

Figure 2 An overview of data analysis



Potential benefits of Big data in Plastic Surgery Research and Clinical Practice

Advantages over traditional research methodologies

Big data research provides several advantages compared to traditional research methodologies(35). Firstly, the large volume of patient data accessible from big data can overcome some of the difficulties in recruiting patients with rare conditions or where there is significant variation in practice(36). The size of such datasets can improve statistical power, reducing the risk of type II errors.

Patients recruited in prospective trials are often subject to selection bias (e.g. healthier and more compliant patients), therefore reducing the translation into clinical practice. From an administrative perspective, big data analysis can be performed at a much faster rate, that is more cost efficient than clinical trials(1).

The use of big data can be utilised to complement traditional research methods. A notable example is that of the identification in a laboratory-based model using rat fibroblasts that wounds that occurred during the night led to delayed healing time compared to day time wounds. This finding was confirmed in humans using the international Burn Injury Database (iBID)(37).

Surgical Outcomes

One powerful use of big data would be to inform patients and professionals alike of the accurate prevalence regarding post-operative complications, such as the average length of stay, patient re-admission rate, venous thromboembolism risks or flap failure. An overview of data driven support tools are summarised in table 3.

Table 3 – Data Driven Clinical Support Tools in Plastic Surgery

Reference	Overview	Method	Results
Esteva et al (38)	A diagnostic tool used to diagnose skin lesions from clinical photographs.	A Deep convolutional neural network trained using 129,450 images of 2,032 lesions.	Accuracy consistent with consultant dermatologists.
IBM Watson (39)	To develop a diagnostic tool to diagnose melanoma from clinical images.	A deep CNN network trained using images from the International Skin Imaging Collaboration (ISIC).	Work currently underway.
Kiranantawat et al (40)	A smartphone application designed for postoperative microsurgery monitoring.	Application taught to analyse skin colour of ischaemic digits from smartphone photographs.	94% Sensitivity at diagnosing venous or arterial occlusion.
Yeong et al (41)	A diagnostic tool designed to predict healing time in burn wounds.	Artifical Neural Networks trained using reflective spectrometry, a technique whereby a probe shines light on tissues and measures the colour and intensity of reflected light of burn wounds.	Predictive accuracy of 86%.

Service planning

The comparison of outcomes between geographical regions would inform service planners, politicians and clinicians on best practices that could improve patient care and resource distribution. In this role, big data has the power to reduce the cost of healthcare. The Getting It Right First Time (GIRFT) programme(42) aims to save the National Health Service (NHS) £1.4 billion by using big data analysis. The programme investigates clinical variations of practice within specialities, comparing these with outcomes to identify best practices. GIRFT analyses data from a number of sources including hospital episode statistics, NHS litigation Authority and relevant data for the speciality. The GIRFT programme is currently underway in plastic surgery.

Public Health

On a population level, big data can inform public health. The incidence of a variety of diseases such as skin cancer and trauma can be closely monitored and allow evolving risk factors to be identified. At present, multiple traditional databases exist in plastic surgery. Analysis of the international Burns Injury Database (iBID) has recently been used to identify detailed demographics and variations of incidence of burn injuries within England & Wales(43).

Litigation

The NHS Litigation Authority (NHSLA), a compulsory database for claims against the NHS, estimates that there are currently over £23 billion of potential negligence claims in process. Big data can be effectively used in the field of litigation, to identify common causes of litigation and thus try to reduce these, along with reducing overall expenditure through reduced claims.

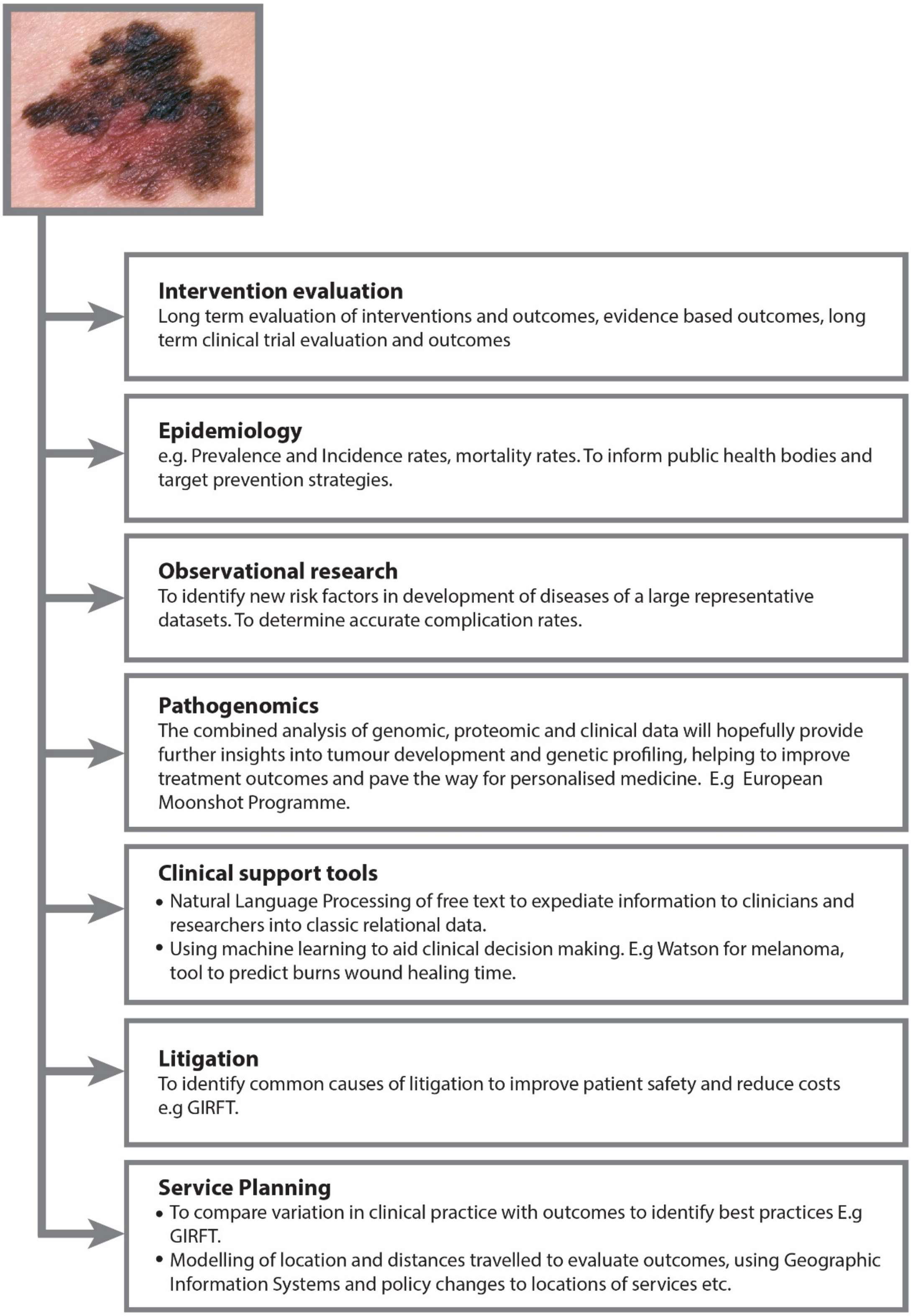
Governance

The plastic surgery community has been faced with several governance challenges over the last few decades, most notably the Silicon controversy, and more recently Poly Implant Prothèse (PIP)(44) and breast implant associated Anaplastic Large Cell Lymphoma (ALCL)(45).

The PIP breast implant scandal is well documented; it is estimated that 400,000 women worldwide received substandard implants. In response, the UK government's Department of Health called for registration of professionals performing cosmetic surgery and for devices(46).

The creation of The Breast and Cosmetic Implant Registry(47) should in time provide a valuable database to improve patient safety, and will become more robust with linkage to EHRs.

Figure 3 An overview of the role of big data in Plastic Surgery using the example of skin cancer.



Limitations of big data

Missing data – Big data commonly deals with data collected for non-research purposes, resulting in incomplete data sets. Assuring full data collection using a Minimum Dataset will be essential moving forward.

Data quality **-** Diagnoses and procedures may be documented using International Classification of Diseases (ICD) codes or via Office of Population Censuses and Surveys Classification of Interventions and Procedures (OPCS-4) codes. The knowledge of such coding systems amongst surgeons is limited, reducing the quality of the data captured or relying on other staff to perform this coding process. Consequently, considerable discrepancies can exist in such data sources as demonstrated in numerous studies(48-51). Extraction of data from unstructured sources using NLP could have significant potential to overcome such limitations.

Statistical analysis – The analysis of large datasets requires unique analytic approaches(51). It must be acknowledged, with such large numbers, statistical significance may not always reflect clinical significance. Furthermore, it has been demonstrated that many studies selectively use data and statistical analysis techniques to emphasise findings consistent with the study hypothesis(52).

Privacy, ethics and security in big data – Considerations surrounding privacy, ethics and security in big data need addressing at the outset, especially give a number of recent high profile concerns such as the 2017 ransomware attach on 80 NHS trusts and hundreds of GP practices across the UK. The attack reportedly cost the NHS £92 million, highlighting the vulnerability of NHS IT infrastructure to Cyber attacks(53).

Currently privacy and data protection laws are based around an individual's control over their information and on principles such as data minimization and purpose limitation. This however does not always fit that easily with the principles of maximizing available data. In May 2018, the European Union implemented the General Data Protection Regulation (GDPR) to strengthen data protection for all individuals in the EU. Researchers can use these data without consent providing appropriate safeguards are in place and that it is permitted under EU law (54).

It is crucial that the public are convinced that once adequate safeguards have been put in place to maintain their privacy and security, big data analysis will provide significant benefits. The launch of the Understanding Patient Data initiative by the Wellcome Trust to improve the public's understanding about the use of healthcare data in research is a welcome development(55).

The Future of Big Data

Big data analytics in plastic surgery is currently in a nascent stage, however as this review demonstrates, the long-term potential is huge. It will be through greater routine collection of data, extraction of unstructured data using techniques such as Natural Language Processing and the integration of these data sources that the greatest breakthroughs will be made. It is important that as a surgical community we understand the potential benefits as well as pitfalls of Big Data, that will in time lead to streamlined services and improve surgical outcomes for our patients.

Acknowledgements

We would like to thank Steve Atherton who produced the illustrations.

This study makes use of anonymised data held in the Secure Anonymised Information Linkage (SAIL) Databank. We would like to acknowledge all the data providers who make anonymised data available for research.

This work was supported by Health Data Research UK, which receives its funding from HDR UK Ltd (grant ref:NIWA1) funded by the UK Medical Research Council, The Royal College of Surgeons of England Pump Priming Award (ISW), Engineering and Physical Sciences Research Council, Economic and Social Research Council, Department of Health and Social Care (England), Chief Scientist Office of the Scottish Government Health and Social Care Directorates, Health and Social Care Research and Development Division (Welsh Government), Public Health Agency (Northern Ireland), British Heart Foundation (BHF) and the Wellcome Trust. This work was also supported by an ESRC award establishing the Administrative Data Research Centre Wales (ES/L007444/1).

Conflicts of Interests

The authors declare no conflicts of interest

References

1. Gandomi A, Haider M. Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management* 2015;35:137-144

2. British Broadcasting Corporation (BBC). Everyone 'to be research patient', says David Cameron. 2011. Available at: http://www.bbc.co.uk/news/uk-16026827. Accessed 25th August, 2017

3. Medical Research Council. Initiatives in informatics research. 2017. Available at: https://www.mrc.ac.uk/research/initiatives/health-and-biomedical-informatics/initiatives-in-informatics-research/. Accessed 25th August 2017,

4. The Royal College of Surgeons. Future of Surgery. The Royal College of Surgeons; 2018

5. Dementia Platform UK. Dementia Platform UK. 2018. Available at: https://www.dementiasplatform.uk/. Accessed 16th November, 2018

6. De Fauw J, Ledsam JR, Romera-Paredes B, et al. Clinically applicable deep learning for diagnosis and referral in retinal disease. *Nature Medicine* 2018;24:1342-1350

7. Connell A, Montgomery H, Morris S, et al. Service evaluation of the implementation of a digitally-enabled care pathway for the recognition and management of acute kidney injury. *F1000Research* 2017;6:1033

8. Ribli D, Horváth A, Unger Z, et al. Detecting and classifying lesions in mammograms with Deep Learning. *Scientific reports* 2018;8:4165

9. Belle A, Thiagarajan R, Soroushmehr SMR, et al. Big Data Analytics in Healthcare. *BioMed Research International* 2015;2015:370194

10. Raghupathi W, Raghupathi V. Big data analytics in healthcare: promise and potential. *Health Information Science and Systems* 2014;2:3

11. Institute for Health Technology Transformation. Transforming Health Care Through Big Data: Strategies for leveraging big data in the health care industry. In: Transformation IfHT, ed. New York; 2013

12. B F, Martin EM, Skotnes T. Big Data in Healthcare Hype and Hope. 2012. Available at: http://www.west-info.eu/pdf/big-data-in-healthcare/. Accessed 25th August, 2017

13. American College of Surgeons. ACS National Surgical Quality Improvement Program (ACS NSQIP). 2017. Available at: https://www.facs.org/quality-programs/acs-nsqip. Accessed 8th August, 2017

14. Public Health England. National Cancer Data Repository. Available at: http://www.ncin.org.uk/collecting_and_using_data/national_cancer_data_repository/. Accessed 15th August, 2017

15. American College of Surgeons. National Cancer Database. Available at: https://www.facs.org/quality-programs/cancer/ncdb. Accessed 15th August, 2017

16. CosmetAssure. About CosmetAssure. 2017

17. Royal College of Surgeons. RCS urges surgeons to apply for cosmetic surgery certification to improve patient safety. 2017. Available at: https://www.rcseng.ac.uk/news-and-events/media-centre/press-releases/apply-for-cosmetic-surgery-certification/. Accessed 12th August, 2017
18. National Trauma Databank (NTDB). Welcome to the NTDB Data Center. Available at: https://www.ntdbdatacenter.com/. Accessed 15th August, 2017
19. int. Burn Injury Database (iBID). Introduction. Available at: int. Burn Injury Database (iBID). Accessed 15th August, 2017
20. Taichman DB, Sahni P, Pinborg A, et al. Data sharing statements for clinical trials. *BMJ* 2017;357
21. Sinnenberg L, Buttenheim AM, Padrez K, et al. Twitter as a Tool for Health Research: A Systematic Review. *American journal of public health* 2017;107:e1-e8
22. Chan M, Estève D, Fourniols J-Y, et al. Smart wearable systems: Current status and future challenges. *Artificial Intelligence in Medicine* 2012;56:137-156
23. National Data Guardian for Health & Care. Review of Data Security, Consent and Opt-Outs. The National Data Guardian; 2016
24. Burton PR, Murtagh MJ, Boyd A, et al. Data Safe Havens in health research and healthcare. *Bioinformatics (Oxford, England)* 2015;31:3241-3248
25. Kelman CW, Bass AJ, Holman CD. Research use of linked health data--a best practice protocol. *Australian and New Zealand journal of public health* 2002;26:251-255
26. Roos LL, Brownell M, Lix L, et al. From health research to social research: privacy, methods, approaches. *Social science & medicine (1982)* 2008;66:117-129
27. Information Services Division. Information Services Division. Available at: http://www.isdscotland.org/. Accessed 7th September, 2017
28. NHS Digital. Our strategy: NHS Digital's strategy for 2015-20. 2017. Available at: https://digital.nhs.uk/article/249/Our-strategy. Accessed 12th March, 2018
29. Ford DV, Jones KH, Verplancke JP, et al. The SAIL Databank: building a national architecture for e-health research and evaluation. *BMC health services research* 2009;9:157
30. The Secure Anonymised Information Linkage Databank (SAIL). SAIL Databank. Available at: https://saildatabank.com/. Accessed 5th August, 2017
31. Lyons RA, Jones KH, John G, et al. The SAIL databank: linking multiple health and social care datasets. *BMC Medical Informatics and Decision Making* 2009;9:3
32. Patel R, Jayatilleke N, Broadbent M, et al. Negative symptoms in schizophrenia: a study in a large clinical sample of patients using a novel automated method. *BMJ Open* 2015;5
33. Patterson O, Hurdle JF. Document clustering of clinical narratives: a systematic study of clinical sublanguages. *AMIA Annual Symposium proceedings AMIA Symposium* 2011;2011:1099-1107
34. Liddy ED. Natural Language Processing. Encyclopedia of Library and Information Science. New York: Marcel Decker Inc; 2001
35. Zhu VZ, Tuggle CT, Au AF. Promise and Limitations of Big Data Research in Plastic Surgery. *Ann Plast Surg* 2016;76:453-458
36. Adkinson JM, Casale MT, Kim JY, et al. So You Have a Research Idea: A Survey of Databases Available for Plastic Surgery Research. *Plastic & Reconstructive Surgery* 2016;137:680-689
37. Hoyle NP, Seinkmane E, Putker M, et al. Circadian actin dynamics drive rhythmic fibroblast mobilization during wound healing. *Science Translational Medicine* 2017;9
38. Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. *Nature* 2017;542:115-118
39. IBM. Researching how to combat melanoma with cognitive technology. 2017. Available at: https://www.ibm.com/blogs/client-voices/ibm-watson-screening-melanoma/. Accessed 18th May, 2018

40. Kiranantawat K, Sitpahul N, Taeprasartsit P, et al. The first Smartphone application for microsurgery monitoring: SilpaRamanitor. *Plast Reconstr Surg* 2014;134:130-139
41. Yeong EK, Hsiao TC, Chiang HK, et al. Prediction of burn healing time using artificial neural networks and reflectance spectrometer. *Burns* 2005;31:415-420
42. Getting It Right First Time (GIRFT). What we do. 2017. Available at: http://gettingitrightfirsttime.co.uk/what-we-do/. Accessed 7th September, 2017
43. Stylianou N, Buchan I, Dunn KW. A review of the international Burn Injury Database (iBID) for England and Wales: descriptive analysis of burn injuries 2003-2011. *BMJ Open* [serial online]. 2015;5. Available from: Ovid Technologies. Accessed 27th February 2017
44. Keogh SB. Poly Implant Prothèse (PIP) breast implants: final report of the Expert Group. 2012. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/214975/dh_134657.pdf. Accessed 7th September, 2017
45. Kim B, Predmore ZS, Mattke S, et al. Breast Implant–associated Anaplastic Large Cell Lymphoma: Updated Results from a Structured Expert Consultation Process. *Plastic and Reconstructive Surgery Global Open* 2015;3:e296
46. Department of Health. Review of the Regulation of Cosmetic Interventions. 2013. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/192028/Review_of_the_Regulation_of_Cosmetic_Interventions.pdf. Accessed 7th September, 2017
47. NHS Digital. Breast and Cosmetic Implant Registry. 2016. Available at: http://content.digital.nhs.uk/bcir. Accessed 6th September, 2017
48. Koch CG, Li L, Hixson E, et al. What are the real rates of postoperative complications: elucidating inconsistencies between administrative and clinical data sources. *J Am Coll Surg* 2012;214:798-805
49. Friel M, Lineaweaver WC. Letter to the Editor. *The Cleft Palate-Craniofacial Journal* 2014;51:365-366
50. Oberlin C, Lineaweaver W. Race and ethnicity in clinical studies. *Ann Plast Surg* 2012;68:545-546
51. Khera R, Angraal S, Couch T, et al. Adherence to Methodological Standards in Research Using the National Inpatient Sample. *Jama* 2017;318:2011-2018
52. Haider AH, Saleem T, Leow JJ, et al. Influence of the National Trauma Data Bank on the study of trauma outcomes: is it time to set research best practices to further enhance its impact? *J Am Coll Surg* 2012;214:756-768
53. Walker D. WannaCry cost the NHS £92 million, report estimates. 2018. Available at: https://www.itpro.co.uk/go/32103. Accessed 20th November, 2018
54. Dove ES, Thompson B, Knoppers BM. A step forward for data protection and biomedical research. *The Lancet* 2016;387:1374-1375
55. Wellcome Trust. Understanding Patient Data. 2018. Available at: http://understandingpatientdata.org.uk/. Accessed 19th May, 2018