

EXTRACTING VALUE FROM BIG DATA IN ORAL HEALTH CARE SERVICES

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Definition of big data

The term big data in healthcare is linked to electronic health datasets, large and complex enough to be managed sufficiently with traditional software, hardware, common data management tools and methods (Frost & Sullivan). Their complexity lies not as much on volume as on the diversity of data types and the required speed at which big data must be handled (Frost & Sullivan). As Boyd et al. (2012) observe, big data is less about massive data than the ability to search, aggregate and cross-reference/compare/analyse big datasets. Defining Big Data in different contexts Boyd et al. (2012) support that technologically the concept relates to the computer processing speed and algorithmic preciseness while analytically the term Big Data refers to the finding of patterns from large data to make economic, technical, social and legal claims. Data sources in healthcare involve clinical data from Computerized Provider Order Entry CPOE and clinical decision support systems (such as physician's written notes and prescriptions, medical imaging, pharmacy, laboratory, insurance and other administrative data), electronic patient records (EPRs), machine generated data (like monitoring vital signs), data from wearable technologies or smart phones apps, blogs (Raghupathi et al., 2013), social media posts (twitter feeds, Facebook updates, webpages and other social media platforms) (Bian et al., 2012) and less patient-centred information regarding emergency care data, news sections and medical journal articles (Raghupathi et al., 2014). According to a report from McKinsey if big data could be fully exploited to improve efficiency and quality in healthcare, the potential gain for the US medical industry would overcome USD 300 billion, dropping the US expenditure on healthcare by over 8% (Manyika et al., 2011).

Sources of big data

Miller, (2012) classifies big data in healthcare according to two main sources; genomics-driven big data including genotyping, sequencing and gene expression and payer-provider big data involving a range of electronic health records, pharmacy prescriptions, patient feedback and responses, and insurance records. Chen et al. (2012) describes the payer-provider category as data matrices of hundreds of thousands of patients with numerous records and parameters such as demographics outcomes and treatments gathered over an extended period of time. According to Gelfand (2011/2012) taking advantage of the knowledge from big data related with health presumes conformance to specific requirements designed by HIPAA (Health Insurance Portability and Accountability Act) and IRB (Institutional Review Board) to build a privacy-retaining and trust-preserving infrastructure for health associated ethical research. Once the challenges of privacy and data protection can be addressed, health related big data like electronic health records will instantly reveal a huge potential in significant clinical knowledge collection and better understanding of patient disease patterns (Chen et al., 2012). Lin et al. (2011) for instance, used EHRs of

approximately 2.1 million records from a large hospital which were selected using International Classification of Diseases (ICD-09) codes. They concluded that in clinically related and valid SDT (symptom-disease-treatment) linkages were evident for seven separate conditions, varying from cancer to infectious and chronic diseases (Lin et al., 2011).

The Vs of big data analytics in healthcare

Volume

Three basic characteristics are embedded in big data analytics, namely volume, velocity and variety (Raghupathi et al., 2014). The huge volume of health care data incorporate personal medical records, radiology images, clinical trial data, human genetics and population genomic sequences as well as more contemporary big data forms such as 3D imaging, genomics and biometric sensor readings (Raghupathi et al., 2014).

Velocity

Velocity refers to the real-time fast pace data capture, storage, manipulation, analysis and comparison for decision making based on the corresponding output (Raghupathi et al., 2014).

Variety

The dimension of data variety concerns the various formats of collected data which can be structured, unstructured and semi-structured. Structured and semi-structured data involve instrument indications and data resulting from the stepwise conversion of paper records to electronic and health medical records while unstructured data contain office medical records, handwritten doctor and nurse notes, paper prescriptions and radiographs etc. (Raghupathi et al., 2014). Structured data in Electronic Health Records (EHRs) and Electronic Medical records (EMRs) use input record fields including the patient name, features of birth, address, physician's name, hospital name, treatment and reimbursement codes as well as other relevant information easily manageable by automated databases (Raghupathi et al., 2014). The huge capacity of big data in healthcare can be achieved by combining traditional with new forms of data both on individual and population level.

Veracity

The fourth characteristic of big data analytics which was introduced by practitioners and researchers refers to veracity, pointing to credibility, reliability and validity of data (Raghupathi et al., 2014). In an industry involving human interventions and treatment decisions, the need for accurate and high quality information is self-explanatory. Higher frequency of poor quality data is observed in unstructured datasets, where imprecise "translations" of flawed handwriting on prescriptions can lead to the wrong data content (Raghupathi et al., 2014). To ensure trust and high quality of data, big data analytics models and techniques, like data mining, statistical processes, algorithms and visualization techniques must consider the characteristic of veracity without presuming that the raw data are always clean, certain and accurate (Raghupathi et al., 2014).

Visualisation and value have been added to the Vs of big data to stress the importance of presenting big data in a visual format that facilitates interpretation. The volume of big data now available is only important if it provides useful and reliable data that can be analysed and interpreted in a way that ultimately adds value to the patient.

Data in Oral Healthcare

The oral healthcare industry generates a substantial volume of electronic data from a variety of sources:

Electronic Health Records (EHR)

Recent legislative changes in the USA since 2004 onwards, have encouraged the adoption and purposeful use of electronic health records (DiGangi, 2012). The result of these changes means that in the USA over 90% of hospitals and 70% of community health services utilise EHR (Basole et al., 2015) and the volume of electronic dental data stored in the USA has increased over this time (Liu et al 2013).

Electronic dental patient records vary according to the design of the information system but generally record those details that would have historically been recorded in paper records including patients demographic details such as name, address, age, gender and medical history, current and historical dental chartings including teeth present, tooth surface status and condition and treatment needs, the condition of the gingiva is also recorded and the system stores radiographs and notes. Details of treatment including both medical and laboratory prescriptions are also recorded.

Available electronically, valid and well constructed patient records can be a useful aid to improve the quality and cost effectiveness of healthcare (DiGangi, 2012)

Claims data

Datasets utilised for health care claims vary from those that capture data from participants enrolled in national or community schemes to those which include data regarding individuals with a specific disease (Stein et al., 2014).

Claims Databases are very variable and often include information regarding some or all of the following (Stein et al., 2014): Diagnostic information possibly utilising International Classification of Diseases codes (ICD-CM), Codes for payments, Patient and provider demographic details and Laboratory and prescription details.

The utility of the claims data for research and planning purposes depends on the nature of the payment system. A determining factor is the scope of data the system requires and even mandates for provider payment and whether the returns are quality assured. For example a capitation payment system where providers are paid a flat fee per registered patient may require less clinical data in its claims forms than a fee per item of service which would be expected to require details of all clinical treatments carried out.

Examples of big data use in oral health

In oral health care electronic data are commonly collected for both recording and payment purposes, these data have been used in a number of ways as described here.

Surveys of oral health have documented the improvements in oral health in established market economies over the last 60 years. Many surveys have used measurement indices employing World Health Organisation standardised criteria. (WHO Oral Health Surveys Basic Methods, 2013). Surveys can be useful for collecting data not available from clinical or claims data and for exploring patient's experience, and preferences, they are helpful for identifying disease associations and can be

hypothesis generating. Survey validity is influenced by the sampling technique, generating a random representative sample of the population of interest is important. Achieving representativeness can be challenging with the need for positive consent.

In an era of survey fatigue it is difficult to attain a high response rate for oral health surveys. In addition, engagement with the population who do not visit the dentist is doubtful as they are unlikely to participate in an oral health survey as they are to visit the dentist. An alternative or supplementary approach to measuring the oral health of defined populations is to derive the data from administrative or claims databases.

In Ireland, Guiney et al (2012) compared the levels of treatment need as estimated among a representative sample of less well off adults in a national epidemiological survey with the levels of treatment subsequently provided in a third party funded scheme for the same population. They calculated the actual treatment levels from a claims database for treatment provided among the population from which the sample was drawn. There were considerable differences among the two with the survey estimating higher treatment need than was subsequently carried out.

In a separate analysis, Guiney et al (2013) examined trends in treatment provision in a scheme for employed adults between 1997 and 2008. The retrospective analysis of claims data over a 12-year-period indicated that the mean number of treatments per patient decreased by 2.0% over time, there were improvements in tooth retention and the number of restorations decreased overall, more oral examinations and prophylaxis were provided each year. These data provide a 'real life' measure of care and can be used to monitor the impact of changing oral health service design on treatment provision and also as a proxy for trends in oral health. The data can also generate useful hypotheses for further testing.

Claims data that are collected partly for reasons of probity such as NHS general dental practice claims forms were utilised by Lucarotti et al. (2005a,b) and Burke et al (2005a,b) to explore factors that affect the longevity of restorations. Analysis of the claims data revealed that the survival period of a restoration was less with increasing patient age, if the patient changed dentist and if the patient was at higher risk of dental decay and attended the dentist more frequently (Lucarotti et al. 2005a,b, and Burke et al. 2005b). Analysis of outcomes of treatment using claims data is not without its challenges as pointed out by Lucarotti et al (2005a) who cited the following limitations in following patients claims over a reference period of time: name changes during reference period; patient seeks treatment privately; patients may emigrate or die; transcription errors from paper claims form to database; patients may change dentist or may not return during reference period. Analysis of claims data adopts a retrospective observational approach to document the outcomes of treatment over time, however other factors which influence treatment outcomes cannot be factored into the interpretation of the data. Examples of such factors cited by Lucarotti et al (2005a) include the choice of intervention which results from an interaction between the dentist and provider, clinical skill and patient factors such as oral hygiene and diet.

Oral health care databases have also been used to examine the impact of interventions on practitioner behaviour. Rindal et al. (2014) examined the changes in practice patterns of participants and non-participants in a Practice-Based Research Network (PBRN). One of the outcomes they looked at was the impact of PBRN participation on implementation of current evidence? Using a combination of electronic dental records and an administrative database they discovered that engagement with a PBRN seems to be an effective mechanism in disseminating and implementing evidence into routine practice (Rindal et al., 2014), the impact of PBRN engagement was found to be greatest for the most highly engaged providers.

A number of studies have progressed to the use of big data (or big data-bases) to explore associations with oral health. These studies are of value in generating new hypotheses about associations, for example the association between oral health and general health as suggested by Jeffcoat et al. (2014). They linked oral health care and general health care insurance records of a carefully selected cohort to estimate possible connections between periodontal therapy at baseline and two outcomes, namely subsequent medical costs and hospitalizations for five systematic conditions over the follow up period (2005-09). The periodontal intervention group were defined as having a diagnosis of periodontal disease and four periodontal treatments in the baseline year (2005). The conditions studied were Type Two Diabetes, Coronary Artery Disease, Cerebrovascular Disease, Rheumatoid Arthritis (T2D, CAD, CVD, RA) and pregnancy (Jeffcoat et al., 2014). They found statistically significant ($p < 0.05$) reductions in the intervention groups for both outcomes for each of the following conditions T2D, CVD, CAD and pregnancy but not RA (Jeffcoat et al., 2014). The analysis was based on claims for 338,891 individuals who had been diagnosed with one of the systemic conditions or pregnancy in 2005 and who had a diagnosis of periodontal disease in 2005 (with no periododontal treatment in 2004). However, the inclusion criteria for the periodontal treatment group limited the intervention group to a small portion (approximately 1%) of patients with the systemic conditions.

The study by Jeffcoat et al (2014) indicates a potentially important association, however lack of information on compliance with healthy lifestyles and therapy for their general condition means that we cannot rule out confounding with the variables truly responsible for the improved outcomes. The 1% of patients defined as the intervention group who completed four periodontal treatment visits in a year, may have been the top performers in terms of motivation and treatment compliance to improve their lifestyle and behaviour to control their disease. Completion of periodontal treatment (as defined for inclusion) may have been a marker for high compliance with maintenance therapy, which reduced medical costs and hospitalisations. Further studies are warranted to further explore the hypothesis generated by Jeffcoat et al's (2014) study.

Fellows et al. (2011) in a Dental Practice-Based Research Network study used electronic insurance claims from 572,606 health plan members, to investigate the association of ONJ (osteonecrosis of the jaw) with treatment with bisphosphonates and other risk factors. Of the cohort 21,164 had treatment with oral bisphosphonates They found 23 cases of ONJ in the entire group and of these 6 (35.3%) had received oral bisphosphonates. In univariate analysis, those exposed to oral bisphosphonates were 15.5 times (CI, 6.0-38.7) more likely to have ONJ than non-exposed patients (Fellows et al., 2011). The results revealed that the absolute risk of ONJ from oral bisphosphonates is low.

Care should be taken in interpreting these results and further studies will be needed to clarify the association because as the authors pointed out the small number of ONJ cases limited their regression results and ability to rule out confounding by indication. They also suggested that future studies will be helped by the introduction of a new ICD code in 2007 "aseptic necrosis of bone, jaw". This new code will facilitate the identification of ONJ cases but that future documentation of onset dates, exposure to potential risks, and healing time would also be important in increasing our understanding of the determinants of ONJ.

The latter two examples illustrate the potential value and current limitations of oral health and general health insurance data. Through elucidating the limitations of these datasets in exploring associations and causation, we can contribute to the design and development of future databases better able to answer important questions regarding disease determinants and the impact of therapy.

Data from mobile devices in combination with electronic patient dental records may be harnessed to improve patient care (Basole et al 2015). The recent development by a dental manufacturer of an application aligned with an electronic toothbrush which uses brushing technique data to improve such a technique (Oral- B, 2016) demonstrates the powerful use of electronic data to improve patient care. This will assist in the process of adopting preventive oral health measures by providing feedback directly to patients.

Against a background of increased capacity to process large databases alongside widespread computerisation of oral health data, a project was developed by European researchers to use available oral health systems data to enhance the focus on prevention of dental disease and to improve oral health.

The “ADVOCATE project”

The ADVOCATE project (Added Value for Oral Health), funded by the European Commission’s Horizon 20:20 program aims to develop strategies for a system transition toward a more patient centred, evidence based and preventive oral health care delivery within the European oral health care systems (Leggett et al., 2016). Based on a partnership of six European Union member states and established collaborations among universities, private insurance companies and state funded health care providers in Germany, Denmark, Hungary, Netherlands, Ireland, the United Kingdom and a biomedical informatics company located in Scotland called Aridhia, the project aims to evaluate the oral health care systems in the member states, provide outcome measurement and promote a preventive approach in oral health care delivery through motivational feedback, economic evaluation and policy recommendations (Leggett et al., 2016).

Big Data use in the ADVOCATE project

Overall, the project explores how the transition toward a more preventive and patient centred oral health system will be achieved through research and the analysis of two data sources: administrative health insurance data and self-reported patient data collected using electronic questionnaires at the dental practice (through a mobile phone or a tablet application) (Leggett et al., 2016). This analysis will evaluate the dental practice performance and outcomes which could then be presented in a dashboard to GPs to provide feedback on the range and type of care delivered to their patients compared with their peers, enhancing potentially their intrinsic motivation to provide more preventive care and further improve their patients oral health (DePasque and Tricomi 2015). A separate analysis of health insurance data from the six EU countries will lead to the assessment of provider payment and patient co-payment schemes on preventive oral health care, drawing on the theory of extrinsic motivation (Leggett et al., 2016). This theory attempts to explain how various financial rewards and remuneration methods (i.e. fee per item, capitation etc.) could be best mixed to improve the quality of care and drive to efficient and effective disease prevention (Birch and Listl 2015, Brocklehurst et al. 2013). Having as its core aim the motivation of dentists to treat patients in a more preventive way, and through the collaboration of six EU member states, the ADVOCATE project is promising long-term benefits in oral health care not only in terms of improved health but also of less invasive treatment leading to useful recommendations for a patient centred integrated oral health system with further positive implications for dentists, policy makers, patients, insurance companies and the general public.

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