Centred on the patient:

Using medical records to improve care

Dr You Chen directs the 'OHPENLab: Optimization of Health Processes and Networks Laboratory' at Vanderbilt University in Nashville, Tennessee. Dr Chen uses sophisticated social network and data mining techniques to mine the vast stores of data held in electronic medical records, identifying patterns representing good practice in the implementation of collaborative patient-centred care. His findings suggest ways both to reduce the cost of healthcare and to improve clinical outcomes for patients.

The cost of healthcare, whether to private individuals, insurance companies or the public purse, is rising around the world. In the United States alone, health expenditure rose from an average of $9,990 per person in 2015 to $10,348 in 2016 and is expected to continue growing by over 5% per year for the foreseeable future.

In the US, at least, one reason for these growing costs is the fragmentation of services such that every intervention is paid for separately (known as the 'fee-for-service' system). This may lead to poor harmonisation of treatments (such as conducting multiple procedures in separate operations rather than bringing different specialities together in a single surgery), unnecessary testing and over-treatment, delays in healthcare provision, and lengthier hospital stays. In short, payment for treatment is dependent on the quantity, not quality, of care received by the patient.

COMMUNICATION, COLLABORATION, COORDINATION

Many experts now believe that a move towards 'value-based healthcare,' in which providers are remunerated based on overall healthcare outcomes, could benefit both patients and those who foot their healthcare bills. However, this value-based model requires a paradigm shift in attitudes to care, from independent clinicians working in isolation, to a patient-centred model based on fully-communicating, collaborating and coordinated care teams. The Optimization of Health Processes and Networks Laboratory, headed by Dr Chen, was established to address the questions underpinning the transition to more coordinated healthcare.

Existing examples of patient-centred care have generally developed through individual specialities creating teams around specific diseases or conditions, and are based upon the knowledge of clinicians and their existing collaborative networks. While effective for certain sets of related conditions, such as heart diseases or gastrointestinal disorders, this approach is often unworkable for patients with more distantly-related sets of complaints. Dr Chen's lab is pioneering an alternative and far-reaching strategy based on 'informatics' (data science). They are developing automated approaches to mine electronic medical records and identify real and potential patterns of collaboration in large, complex medical institutions. Because electronic medical records capture not only medical details, but information sharing, coordination and documentation, this approach can provide insights into a multitude of operational activities involving a diverse range of staff, patients and conditions within the healthcare system.

Figure 1. Leveraging electronic medical records to learn a bird's eye view of VUMC's collaborative care teams (colour clusters) and their constituent operational units (nodes in the network). The teams include: *Interventional Cardiology and Vascular; Vanderbilt Psychiatry; Neuroscience; Infection; Oncology; Paediatrics Cardiology, Comprehensive Care and Neonatology; Vanderbilt Emergency Medicine; Trauma Center; Women and Babies; Nephrology;* and *Gastroenterology.*

PHENOTYPES CHARACTERISING MULTI-CONDITIONS OF A PATIENT

Dr Chen has identified four main challenges to the implementation of coordinated, patient-centred care, which informatics approaches could help to solve. The first challenge is that it may not be immediately obvious which health conditions need to be treated in a coordinated manner, i.e., which conditions tend to co-occur in the same patient. At the same time, there is a lack of standards to characterise multi-conditions of patients in different institutions.

Chen and his team have developed an artificial intelligence approach based on a data mining strategy known as 'latent Dirichlet allocation' to learn 'topics' characterising patients' multi-conditions and test their transferability across two very different healthcare institutions (Vanderbilt University Medical Center (VUMC) in Nashville, and Northwestern Memorial Hospital in Chicago). The methodology allowed them to define 25 health condition 'topics' which could be identified from both sets of data. Their findings show a patients' multiple health conditions can be characterised by 'topics'; and the 'topics' learned from one institution can be transferred to another, allowing more reliable comparison of patients' health problems and treatment needs.

HIDDEN INTERACTIONS

The second challenge Chen recognised is that care teams, even where they exist, are seldom explicitly defined within a healthcare institution. Even intensive observational studies can easily miss collaborations occurring across medical specialities, those that occur on an ad-hoc basis, or those that take place virtually, via a reading of other clinicians' notes in electronic format.

Here, Chen's automatic, unsupervised machine learning techniques were able to extract information on which healthcare staff viewed each of almost 18,000 patients' records over a four-month period at VUMC. A network analysis technique was then used to identify patterns of association between clinicians viewing similar records. The results suggested that, although the patients between them
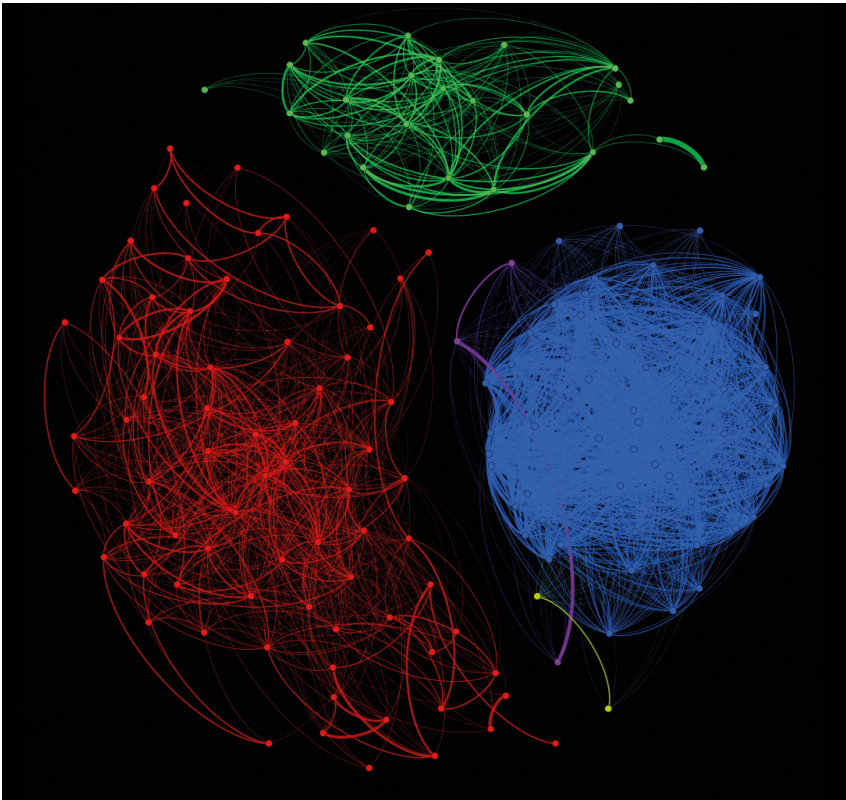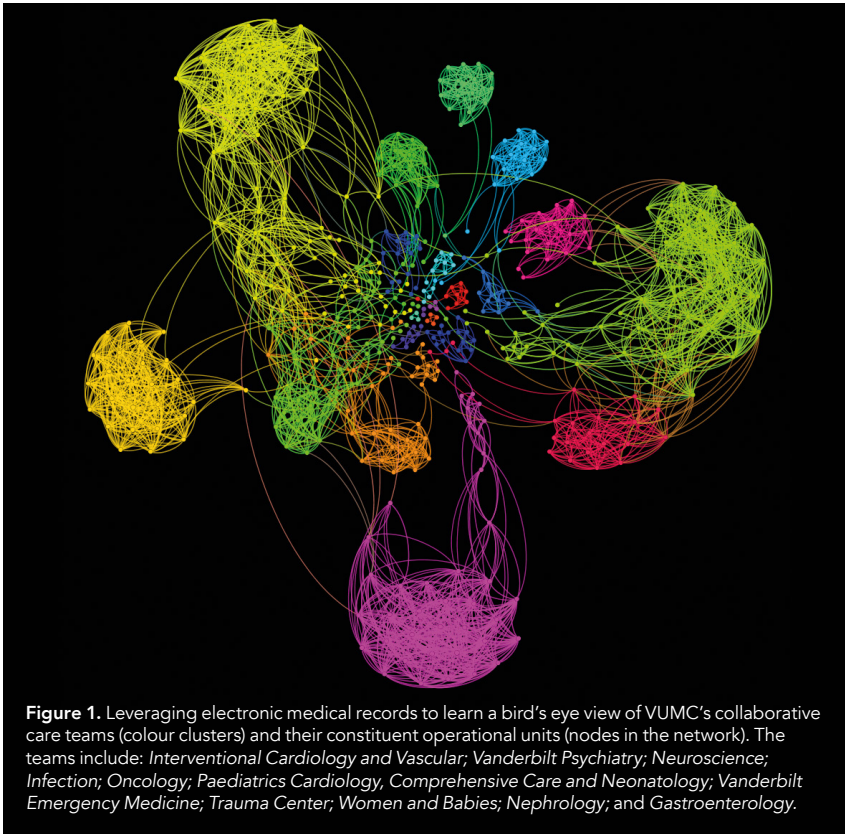

Figure 2. Three major components of trauma care team learned from electronic medical records of patients receiving trauma service from VUMC. **Blue:** acute care, a mix of healthcare employees from "emergency", "anaesthesiology", "cardiovascular", "transplant center", "acute renal failure", "orthopaedics" and "surgical intensive care unit". **Green:** post-acute care including employees from "internal medicine", "special education" and "social work"; **Red:** rehabilitation care including employees from "center for human nutrition", "rehabilitation service", "psychiatry" and "physical medicine & rehab department".

Electronic medical records capture not only medical details, but information sharing, coordination and documentation.

exhibited over 1,400 different types of diagnosis, the medical staff treating them tended to work in only 34 collaborative groups, which could be considered as care teams. When the 34 groups were presented to healthcare staff, they agreed that the computational findings were plausible in a clinical setting.

THE RIGHT TEAM

Even where care teams are already well-defined, Chen has detected a third problem: matching patients with particular conditions to the right team to ensure that patient-centred care works most effectively. The lab's solution to this problem involved drawing on the results of the previous two challenges: they designed a machine learning framework to analyse health condition patterns across patients in terms of the 25 health condition topics identified in the first challenge and the workflow patterns of the clinical care teams identified in the second challenge.

From this, they were able to identify four key 'collections' of medical needs: foetal abnormalities, problems in late pregnancy, prostate problems, and a mix of chronic, largely heart-associated conditions. Their model showed that each area of medical need was clearly associated with a particular set of care teams and healthcare staff interactions. For example, patients falling within the 'foetal abnormality' collection tended to be associated with specific interactions between doctors, nurses, anaesthetists, pharmacists, radiologists, and medical secretaries – interactions which can now be promoted in the treatment of these

Figure 3. The association network between medical needs (pi) and care teams (wj). The four areas of medical needs (shown in Blue, Green, Purple and Red) are: Green: foetal abnormality leads to complicated pregnancy and additional delivery problems (e.g., foetal distress), which requires interventions, such as those provided by the birth trauma service. Red: late pregnancy suggests a larger size infant requiring intervention (e.g., use of suction or forceps), which can cause temporary skull injuries. Purple: anaemia and hypogonadism are often complications of prostate cancer and can lead to bone loss. When the thyroid does not produce a sufficient amount of hormones, it can cause lower esophageal sphincter dysfunction. This allows stomach contents and digestive juices to enter the esophagus, which may lead to gastroesophageal reflux disease. Blue: cerebrovascular disease and coronary atherosclerosis are the most common cause of congestive heart failure (CHF); smoking and diabetes are associated with all three diseases. Depression is associated with coronary disease. Liver test abnormalities and renal failure may occur with CHF.

p20: Anemia connected
p11: Prostate connected
w10   p7: Osteoarthrosis
p13: Cancer   w19   w16
p18: Essential hypertension and hyperlipidemia
p21: Gastroesophageal reflux disease
p3: Hypothyroidism connected
p14: Cerebrovascular disease
p19: Tobacco and alcohol connected
w23
p6: Diabetes
p8: Urinary infection connected
p15: Depression
p23: Coronary atherosclerosis
p5: Thrombosis connected
p4: Oncology
p16: Heart failure
w24   p22: Liver disease
p25: Kidney disease
w7
p10: Sepsis
w4

p1: Skull associated injury
p2: Child birth
w15 w25
p9: Late pregnancy
p24: Mother complicating pregnancy connected
w3 w13
w20
p17: Fetal abnormality
p12: Birth trauma
w22   w14   w11

patients to ensure more appropriate and effective patient-centered care by the best-matched 'bundle' of healthcare staff.

SEEING REAL BENEFITS
The fourth and final challenge that Chen believes needs to be met in order to roll out patient-centred, value-based healthcare, is to be able to evaluate and measure the clinical and financial impacts of different care team models. One key measure that can be used as a proxy for healthcare cost and effectiveness is the length of a hospital stay. This is particularly true for trauma patients (those suffering sudden physical injury rather than illness), with trauma-related hospitalisations being the most expensive in the US.

Chen and his team used statistical clustering and regression techniques to quantify the relationship between healthcare staff interactions (i.e., communications within care teams) and the length of hospital stay for more than 5,500 hospitalised trauma patients at VUMC. They found a remarkably clear distinction in outcomes: those patients experiencing the largest quantity of collaborations between healthcare staff had the shortest hospital stays, while those subject to fewer interactions (i.e., supported by less well-integrated care teams), spent much longer in hospital, indicating greater financial cost as well, of course, as pain, distress and inconvenience to the patient.

The treatment of trauma patients often involves a complex mix of specialists such as surgeons, respiratory specialists, emergency room doctors, radiographers, neurosurgeons, anaesthetists and nurses. Chen concludes that "robust and reliable interactions among such healthcare employees can reduce the length of hospital stays." The ability to quantify these interactions will help healthcare organisations, he says, "to refine or influence interaction structures in a manner that reduces clinical resource consumption."

A DATA REVOLUTION
In solving these four challenges (and undoubtedly more in the future), Dr Chen's innovative methodologies and technologies have been able to exploit the vast, hitherto underused resource of electronic medical records.

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The virtual insights 'learned' from his automated programmes provide real opportunities to optimise healthcare activities. While automated data-mining can provide a basis for discovering opportunities to improve, streamline and coordinate care, Chen is quick to point out that, "Translating such findings into actual care management will require further refinement, implementation, and evaluation."

Ultimately, for the most complex patients exhibiting multiple health conditions simultaneously, the informatics approaches pioneered by Chen and his team provide support, information and evidence to help healthcare institutions ensure that the best, patient-centred care team is in place. In the future, their methods may even be able to predict diseases – such as neonatal conditions – that are otherwise hard to spot, enabling clinicians to intervene earlier and potentially improve clinical outcomes for patients.

Behind the Research
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Research Objectives

The goals of this collaborative research project are to 1) model clinical phenotypes to characterise health conditions of each individual patient, 2) learn collaborative care teams, and 3) infer associations that may exist between the cost of care and team structures.

Detail

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Bio
You Chen is an Assistant Professor of Biomedical Informatics at Vanderbilt University. He is the director of the OHPENLab. His ultimate goal is to leverage medical data (e.g., electronic medical records), health information technology (e.g., mobile health, Restful API) and computational model (e.g., social network analysis) to build patient-centred care.

References

Chen Y, Lorenzi N.M, Sandberg W.S, et al. (2017). 'Identifying collaborative care teams through electronic medical record utilization patterns'. *J. Am. Med. Inform. Assoc, vol.* 24, issue e1, pp. e111-e120. https://doi.org/10.1093/jamia/ocw124

Chen Y, Ghosh J, Bejan C.A, et al. (2015). 'Building bridges across electronic health record systems through inferred phenotypic topics'. *J. Biomed. Inform,* vol.55, pp.82-93. http://dx.doi.org/10.1016/j.jbi.2015.03.011

Chen Y, Kho A.N, Liebovitz D, et al. (2018). 'Learning bundled care opportunities from electronic medical records'. *J. Biomed. Inform, vol.*77, pp.1-10. https://doi.org/10.1016/j.jbi.2017.11.014

Chen, Y., Patel, M.B., McNaughton, C.D., et al. (2018). 'Interaction patterns of trauma providers are associated with length of stay'. J. Am. Med. Inform. Assoc. (online ahead of print). https://doi.org/10.1093/jamia/ocy009

Personal Response

What can electronic medical records tell us that clinicians can't?

❝ Electronic medical records (EMRs) are contributions from a combination of clinicians, patients, healthcare organisations, and health information technologies. The EMRs generate more information than a clinician can provide. Three typical questions raised by patients that the EMRs can answer but clinicians seem unable to are the following:

1. Who are patients similar to me? EMRs contain a substantial amount of detail about a patient's medical history and conditions that can be used to identify similar patients.

2. Where's my care team? EMRs document clinical communications, medication management activities, and information exchanges between healthcare professionals, which can be used to learn who worked with whom.

3. What are potential risk factors associated with my health? EMRs can be used to predict diseases and identify potential risk factors associated with them. ❞

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