Harnessing the full spectrum of digital data to support the delivery of personalised services across the health care continuum

White Paper

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February 2019

Digital Health Cooperative Research Centre
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Introduction

Like many other aspects of society, health care is rapidly digitising, which is changing the way in which health services are delivered and the type of services available. Consumers collect data that can inform the delivery of health services through wearable and mobile devices. Health care delivery settings are becoming more fluid with many health care interactions now occurring outside of physical facilities using telehealth and digital applications. Technological change also provides new ways for providers to monitor health status remotely and provides new opportunities for earlier intervention. The aim is to take advantage of data and technological developments to keep people healthier for longer and ensure access to high-quality care that is tailored to a person’s individual clinical, biological and lifestyle profile.

The purpose of this paper is to describe the data sources\(^1\) that can be used to improve and manage health across the health care continuum, in particular how genomic data and data from consumer-facing applications can be bought together with the event-based data that are routinely collected in clinical settings. Additionally, the paper provides an overview of technologies now available to leverage these data sources to inform the delivery of health care and provides examples of how these data sources and technologies have been applied to improve the planning and delivery of health services across the health care continuum. This paper is aimed at both health service planners and researchers working across clinical and public health settings and technologists who have expertise in computer science and engineering who see new opportunities in the digital health sector.

\(^1\) In this paper, data refers to digital data in all forms, both structured and unstructured data types.
Outline of paper

Section 1: This section discusses the changing nature of health care and how emerging technologies provide new opportunities to use digital data to inform health care delivery across the care continuum.

Section 2: This section describes the health care continuum across the stages of health promotion and prevention, treatment and maintenance. While most health data have traditionally been collected during treatment, there is an increasing variety of data collected that can be analysed to inform all stages of health care delivery.

Section 3: The different categories of information and the new and existing data sources that generate information that can be used across the health care continuum are explained in this section.

Section 4: Major technologies that make sense of data and translate data into insights to inform increasing personalised, consumer-focused care are discussed. The section focuses on artificial intelligence, analysing ‘Omics information and the enabling infrastructure for information discovery.

Section 5: Bringing together the findings of the four previous sections, the final section presents a series of use cases to demonstrate how new technologies are being applied to a variety of data sources across the health care continuum.

Section 6: Summarises the topics covered in the White Paper and discusses the role of the Digital Health Cooperative Research Centre (DHCRC).
Section 1: The changing nature of health care

Much of modern medicine focuses on the treatment of illness rather than the prevention of illness. This bias also extends to the collection of health data. A vast array of data focused on the delivery of treatment services are routinely collected by hospitals, health insurers and other health care providers. We are beginning to unlock these data and discover their utility for understanding and informing health service use, developing funding and payment models, and supporting policy formulation at the population level [1-4].

In order to gain insights on the efficacy of specific treatments or patient outcomes at an individual level, the data collected routinely in health care are inadequate, as the data are coarse and not ‘content-rich’ and do not reflect the individual as a whole. These data are often aggregated or summarised and lose granularity of information. Additionally, the clinical details currently collected and stored in an individual’s electronic health record are event based and do not usually reflect the genomic makeup of the individual or social and environmental factors that could be impacting an individual’s health status. As a result, genomic and social and environmental factors are rarely used in clinical settings to inform care.

With the increasing disease burden caused by chronic conditions that are often preventable with specific interventions, there is increasing attention being paid to moving the health system upstream and investing in more preventative measures that may reduce the need for treatment altogether. Additional data sources reflecting social and environment factors pertaining to an individual and genomic information can help develop targeted programs in health promotion and prevention.

Although, it has long been recognised that multiple factors contribute to disease occurrence and progression, the health care system had few mechanisms to collect information on additional factors such as a person’s genotype, (reflecting their internal health status) and their environment and their lifestyle (reflecting external factors and often referred to as the social determinants of health). With genome sequencing technologies becoming more accessible and a whole range of consumer applications that capture external environment and lifestyle factors now available, we now have a full spectrum of data that can drive insights to manage the entire health care continuum of an individual from prevention to treatment. It has been argued that the importance of aggregating genomic and related data with health care outcomes cannot be overstated [5].
Section 2: The health care continuum

The disease burden across the world is shifting towards non-communicable or chronic diseases including cardiovascular disease and diabetes. Accompanying this shift is greater recognition of the health system’s role in both preventing illness and promoting health. In this paper, we refer to the health care continuum and categorise three broad stages in which health services are needed – Health Promotion and Prevention, Treatment and Health Maintenance. These stages were adapted from a model originally developed to describe stages of care for mental health and substance use conditions but can be applied more broadly to a range of chronic health conditions [6,7]. The model is useful for planning health services as it describes the different types and levels of service needs required across the population at a particular time.

[Figure 1. Stages of the health care continuum (adapted from Institute of Medicine, 1994)]

Health promotion and prevention

Health interventions that aim to prevent the occurrence of a specific condition and promote health and wellbeing by enabling people to increase control over, and improve, their health. Prevention initiatives can be divided into three categories [8]:

1. Universal: Targeted at the general population or a segment of the entire population with an average risk of developing a disease or health condition such as messages reminding individuals of recommended physical activity levels and nutrition standards.

2. Selective: Targeted at specific sub-groups within the population that have higher than average risk of developing a disease or health condition such as smoking cessation interventions.
3. **Indicated**: Targeted at identified individuals with early stage indicators or detectable symptoms of a disease such as weight loss interventions for people with higher than average body mass index or interventions for people with hypertension.

**Treatment**
Health interventions aimed at people who are unwell with specific signs and symptoms of a disease or health condition. Treatment interventions include assessment, diagnosis, treatment planning and delivery, often involving multiple health professionals. Care delivered at the treatment stage is commonly divided into three categories [9,10]:

1. **Primary Care**: Care that represents the first point of contact with the traditional medical system. Primary care is generally provided by general practitioners, allied health professionals and pharmacists in community settings for less severe or less urgent conditions. Emergency department care may also be the first point of contact for unexpected and/or urgent medical conditions.

2. **Secondary Care**: Care that is provided by medical specialists or other health professionals following the first contact of a patient with another health practitioner in primary care. Secondary care may be provided in a hospital or clinic. Care may be provided by professionals with specialised expertise in a particular body system or area of medicine such as psychiatry or cardiology.

3. **Tertiary Care**: Care that is highly specialised, usually delivered as an inpatient in a hospital setting. Tertiary interventions include complex medical and surgical procedures.

**Health maintenance**
Health services that are provided following a treatment intervention including:

1. Ongoing support and monitoring adherence with a treatment plan
2. Rehabilitation to restore health and functioning following treatment.

Both medical and allied health practitioners may provide health maintenance interventions in hospital or community settings. Interventions can also be led by patients outside of formal care settings such as exercises to restore physical functioning with guidance provide intermittently by health professionals.

People may move between the different stages of the health care continuum for the same condition over time and at a particular time, a person may be in different stages of the continuum for different health conditions or diseases.
Risk identification
Targeting interventions across the health care continuum involves assessing and identifying an individual’s health risks. Risk is routinely considered in clinical practice at all stages of the care continuum from GPs assessing a person’s blood pressure and cholesterol levels against guidelines to identify risk of cardiovascular disease to a surgeon assessing a person’s age, weight and physical activity levels prior to performing a surgical procedure.

In prevention and health promotion, risk identification often occurs as a process of identifying target groups within a defined population for interventions based on indicators of health risk such as age, health status and levels of health service use. Interventions are then implemented for different target groups that are appropriate to the level of health risk [11].
Section 3: Digital health data environment

Across the health care continuum, the rapid evolution of technological solutions to both collect and analyse increasingly large and diverse data sources has opened up new opportunities to inform the delivery of health services. There have been a number of recent reports released on the future of medicine that incorporates the greater use of digital data to inform the planning and delivery of health care, particularly incorporating information from genomic data through precision medicine initiatives [5,12].

While many health care interactions still involve writing manual clinical notes, referral letters and transferring results via telephone or fax machine, we are quickly moving to an environment in which all data collected in health environments are captured, stored and analysed in electronic or digital format.

Information categories and data sources across the health care continuum
An important starting point is the information needed for planning and delivering services personalised to individual needs across the health care continuum. As discussed in the Introduction, much of the data that are routinely collected in health care settings are collected at the treatment stage relating to a person’s direct use of health services across primary care, specialists, emergency departments and hospitals. Information on signs, symptoms and diagnosis of disease are often directly recorded (or automatically populated from diagnostic tools) within the electronic medical record (EMR) at the point of health care delivery.

Electronic Medical Records
The EMR, used in primary, secondary and tertiary treatment settings, contains a range of information including a patient’s medical history, diagnoses, medications, treatment plans, radiology images and laboratory test results. The EMR contains various types of data including measurements, medication use, images and clinical notes. The volume of data stored within the EMR is rapidly increasing along with the types of data including both biological and genomic data. A major challenge lies in selecting from the vast array of data contained within EMRs and combining these different types of data to support clinicians in their decision-making about care planning in real-time.

While increasingly sophisticated techniques to collect data related to treatment interventions exist, the processes for collecting data that informs the other stages of the health care continuum, prevention and maintenance are less mature. Standardised and comprehensive data for an individual are not routinely collected outside the treatment setting. However, this situation is starting to
change. Data are increasingly being collected via sensors and applications embedded in wearable devices and smart devices, part of a growing category of products dubbed the Internet of Things (IOT).

The Internet of Things
IOT refers to the combination of object identification technologies, wireless networks, sensors, embedded systems and nanotechnologies to connect things in the world so they can be tagged, sensed and controlled over the internet [13]. IOT devices collect data actively from consumers via their direct input of data into applications and also passively record environmental or geographic data via sensors. These devices can provide information on lifestyle factors that may impact health including diet, physical activity and emotional wellbeing but may also support a person to manage their health through reminders and telehealth consultations. Across all aspects of the health care continuum, social and environmental factors such as a person’s living arrangements, social supports and environmental exposures are important to consider in supporting planning and delivering health services. IOT devices can be a valuable source of this information.

Omics’ data
The increasing use of ‘Omics in health holds promise in revealing new information on the biological pathways of disease. This paper focuses on the use of data from a subset of ‘Omics disciplines – genomics, phenomics and metabolomics (although, there are other ‘omics disciplines). Genomics analyses the information relating to an individual's genomic makeup including their DNA and RNA. Phenomics studies expressed biological, physiological and behavioural traits that account for variation in disease expression. Metabolomics studies the small molecules in biological tissues or fluid that may act as diagnostic tools for health conditions [14].

Biological factors contributing to disease are currently underestimated in clinical practice [15]. This results in the treatment process for a single disease often being similar for different types of patients, even though the disease process itself is highly complex and likely caused by the interaction of different factors. Methods that evaluate the interaction of genotype and environmental factors are likely to better indicate how a patient will respond to a treatment.

The data sources available across the health care continuum are summarised in Figure 2 below.
Structured and unstructured data

Before discussing the technologies for analysing health data sources, it is important to distinguish between data types. A high-level distinction is between structured and unstructured data.

**Structured data** are data that are organised into specific schema. There are two types of structured data:

- Numerical data used to measure height and weight or count the number of hospital admissions.
- Categorical data that represents characteristics such as smoking status or education level.

Structured data are often stored within relational databases and a range of established statistical analysis software exists for structured data including Excel, SQL and SAS [16].

**Examples of structured data in health care:**

- Standardised data fields collected in patient registration systems and clinical registries
• Responses to questions in validated survey instruments to monitor health status and symptoms such as the EQ-5D quality of life measure, Kessler-10 depression and anxiety screening tool.

**Unstructured data** are not structured via pre-defined data models or schema but have internal structure. The media of unstructured data may be text-based or non-text-based including images, audio and video. Although research techniques to analyse unstructured data have existed for many years, the widespread analysis of unstructured data, including in the health sector, has been relatively limited [17].

Examples of unstructured data in health care:

• Diagnostic images and videos including X-rays, MRIs and ultrasounds
• Clinical notes
• Audio and video recordings from telehealth interactions

Increasingly, the distinction between the collection, storage and use of structured and unstructured data is starting to converge. Images and other multimedia content are being stored in structured databases and there are additional content-based search facilities used to analyse unstructured data stored within structured databases.
Section 4: Technologies
The previous section identified data sources and categories of information in the digital health environment that provide new opportunities for informing interventions across the health care continuum. There are an increasing variety and volume of data types including both structured and unstructured data originating from a variety of devices. As a result, using and optimising methods, techniques and supporting infrastructure capabilities are essential to make sense and harness the value of data and translate data into insights to inform personalised health care. This section focuses on three technologies: artificial intelligence, analysing ‘Omics information and enabling infrastructure for information discovery.

Artificial intelligence
Artificial intelligence (AI) is a broad term referring to a collection of methods to combine, process and make sense of large amounts of data. A more comprehensive overview of the potential applications of AI to health can be found in the Digital Health CRC Technical Paper, AI and Health [18]. This section focuses on machine learning, a major subfield of AI. Examples of how machine learning techniques are being applied across the health care continuum are included in Section 5.

Machine learning is the science of getting computers to dynamically learn and act without being explicitly programmed. Machine learning is widely used today to power search engines and recommender software and encompass a broad range of techniques. There are two main types of learning models: supervised and unsupervised [19].

Supervised learning models or algorithms are used when we have prior knowledge of a specific outcome or target. The goal of the algorithm is to learn functions that can predict the output using a defined set of variables or factors that may affect the outcome. Classic examples of supervised learning methods include classification and regression.

In unsupervised learning models, there are no labelled outputs and data are analysed without a specific outcome or target defined. The goal is to infer natural structure within a set of data points. Mathematical techniques of clustering and dimensionality reduction are used in unsupervised learning as no labels are provided in the original data. Dimensionality reduction refers to the methods used to represent data using less columns or features.

Deep learning, a member of the broader machine learning family, uses neural networks to learn complex patterns in large amounts of data. Neural networks involve techniques that find connections
between data units and derive meaning that may be used for decision-making processes. Deep learning techniques are often used while dealing with large volumes of unstructured data such as texts and images and are often used in image recognition and natural language processing applications [20].

Genomic and ‘Omics related technologies
The technological advances in genome sequencing and the rapid decline in the cost of sequencing has led to the increased use of genomic information in healthcare. Genome sequencing involves determining the order of the chemicals that form the DNA molecule – the carrier of genetic information in living organisms. Sequencing techniques may target a specific stretch of DNA referred to as short-read sequencing or in the case of long-read sequencing, produce a single continuous read or piece together shorter fragments, which provides more complete genomic information but is also more costly [5, 21].

Although there are only a small number of diseases with large genetic components (e.g. Down’s syndrome, Fragile X syndrome, Huntington’s disease), genomic information can be used to inform treatment pathways for certain conditions with the most advanced work in this area occurring in cancer. An example is the use of trastuzumab (herceptin) for HER-2 (human epidermal growth factor receptor 2) positive breast cancer that has greatly improved outcomes for patients with a tumour presenting amplification of the HER-2 gene. Genetic screening can improve the targeting of appropriate treatment for patients with HER-2 positive breast cancer but it should be recognised that this is only one type of breast cancer and even some patients with HER-2 positive breast cancer do show resistance to this therapy [22]. Additionally, gene therapy has been used to treat diseases such as a variant of haemophilia (known as haemophilia B) with promising results [23].

Our genes alone are rarely the sole cause of disease. Instead, diseases occur due to complex interactions between our genes and the environment. Genome-wide association studies (GWAS) attempt to identify the genetic variables associated with a specific observed disease state (phenotype). This is known as a phenotype to genotype approach. The phenotype is the ensemble of observable characteristics displayed by an organism. The word phenome is sometimes used to refer to a collection of traits, while the simultaneous study of such a collection is referred to as phenomics.

Through phenome-wide association studies (PheWAS), a similar, complementary approach is being used to try and map a single genetic variant with many different phenotypes, known as a genotype to phenotype approach. As depicted in the Figure below, phenotype information can be defined by a
range of data often included in an EMR such as diagnostic codes, clinical test results and clinical notes [24]. However, it should be noted that there are currently challenges in phenotyping due to the fragmentation of data sources across the health system and the challenges in accessing and linking relevant data sources across organisations. These challenges in the Australian health context are further discussed in a recent Digital Health CRC report, Flying Blind Volume 2 [25].

Figure 3 illustrates the differences between GWAS and PheWAS approaches. A GWAS begins with a phenotype of interest and systematically analyses variants across the entire genome (i.e. “genome-wide“) for association to the phenotype. GWAS can identify multiple genetic associations to a specific phenotype. A PheWAS begins with a genetic variant of interest and systematically analyses many phenotypes (i.e. “phenome-wide”) for association to the genotype. PheWAS has the ability to identify multiple independent phenotypes associated with a single genetic variant. [26].

Figure 3. Genome-wide association studies (GWAS) and phenome-wide association studies (PheWAS) (Image from Robinson et al 2016 [26] used under a creative commons license.)

There is also increasing attention paid to the study of metabolites, which are the small molecules in cells, biofluids and tissues, to provide diagnostic biomarkers of disease. Metabolites are the product of the genome that are most proximal to the phenotype or expression of the gene, so may be an important source of novel markers and predictors of disease [5].
New methods to combine genomic, phenomic and metabolomics data sources are being researched, which may further explain biological pathways of disease in individuals in the future. Combining genomic, phenomic and metabolomic data has the potential to not only personalise treatment but also allow more proactive preventive interventions that are targeted to each individual based on their risk factors.

Ideally, the approach starts with PheWAS that characterises the clinical phenotypes associated with the condition of interest. Analysis of genomic profiles may identify genetic variables associated with each phenotype, which may be further refined or supplemented with metabolomic analysis before and during treatment. This analysis may identify factors associated with treatment efficacy such as therapeutic drug response [14].

**Enabling infrastructure for information discovery**
Effectively assembling and analysing the increasing volume and variety of longitudinal health data requires infrastructure capabilities that can enable information discovery to support care across the health care continuum.

The infrastructure that can enable information discovery should offer the following functionalities:

- Ability to support a variety of data types including data from:
  - IOT devices (e.g. biomedical, telemedicine and home/place-based sensors)
  - Consumer volunteered Information collected via digital applications
- Data sharing capability
- Ability to process complex datasets
- Ability to handle off-the-shelf tools and standards for health data processing (e.g. tools for data cleaning, implementing interoperability such as FHIR discussed later in this section)
- Ability to support agile data documentation.

Following data collection, the data need to be stored and, in most cases, transferred and processed in some way before being used for machine learning and other analytic techniques. Careful attention needs to be paid to data collection phases, what was collected, how, when, where and by whom. Inconsistencies in data collection can affect the quality, accuracy and reliability of the data and by extension, how others can use it [5].

The sensitive nature of health information (protected by legislation in many jurisdictions including Australia) also means that privacy and data security considerations are paramount in building
enabling infrastructure. Issues relating to privacy and data security in the collection, storage, transfer and analysis of data are discussed in Flying Blind Volume 2 [25]. Figure 4 provides an overview of such an enabling infrastructure based on recommendations for the Australian context made in the Productivity Commission Report on Data Availability and Use [27].

**Figure 4.** Conceptual architecture for enabling infrastructure using multiple sources of health data
Advances in computer processing power and storage have seen the development of highly secure cloud-based solutions for managing large amounts of structured and unstructured data beyond the traditional format of relational databases. Particularly important in this rapidly changing environment are methods for linking and bringing together data from different sources on a dynamic basis. A major development in this space is the introduction of the Fast Health care Interoperability Resources (FHIR) specification, a standard for exchanging health care information electronically. As a common data model is needed to develop integrated datasets on which to apply AI techniques, FHIR has been adopted as the standard for transferring data by an increasing number of technology developers in health care including Google [28].

Summary of technologies
This section reviews advances in technology in three areas that facilitate the use of diverse data sources to improve and manage health across the health care continuum. AI techniques are increasingly being applied to large amounts of data collected routinely in the course of health care delivery and health management. An increasingly important source of data are ‘omics data, which are increasingly being used in research and practice to personalise health care. Genome sequencing techniques and association studies to examine genotype-phenotype and metabolite interactions are deepening our understanding of the interplay of genomic, biological and environmental factors contributing to disease. Finally, the infrastructure for enabling information discovery is a crucial component underlying the application of both AI and ‘Oomics. Considerations for infrastructure development include the capabilities to process large amounts of data of different types, ingest and share data from different sources on a real-time basis and interface with a range of off-the-shelf tools and interoperability standards.
Section 5: Use cases across the health care continuum

Bringing together the content from previous sections, this section discuss how new technologies are being applied to the emerging sources of data and information categories across the health care continuum. These use cases, summarised in Table 1, can:

- Enable earlier detection of disease and disease risk
- Personalise treatment using diverse data sources
- Support health maintenance and rehabilitation in the community.

Table 1. Use of data and technologies in use cases across the health care continuum

<table>
<thead>
<tr>
<th>Use Cases</th>
<th>Data</th>
<th>Technologies</th>
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<tr>
<td>Prevention and Health Promotion Enabling earlier detection of disease risk</td>
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<tr>
<td>Risk of opioid misuse</td>
<td>Clinical records</td>
<td>’Omics sequencing and techniques</td>
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<tr>
<td>Diabetic complications</td>
<td>’Omics sequencing and techniques</td>
<td>’Omics sequencing and techniques</td>
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<tr>
<td>IOT and wellbeing</td>
<td>Artificial intelligence</td>
<td>Artificial intelligence</td>
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<tr>
<td>Treatment: Using diverse data sources to personalise treatment</td>
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<tr>
<td>Type 2 Diabetes management</td>
<td>Clinical measures</td>
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<tr>
<td>Personalising cancer care</td>
<td>’Omics sequencing and techniques</td>
<td>’Omics sequencing and techniques</td>
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<tr>
<td>Targeting drug therapy</td>
<td>’Omics sequencing and techniques</td>
<td>’Omics sequencing and techniques</td>
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<tr>
<td>Maintenance: Support health maintenance and rehabilitation in the community</td>
<td></td>
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<tr>
<td>Community dementia care</td>
<td>Clinical records</td>
<td>’Omics sequencing and techniques</td>
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<tr>
<td>Remote cardiac rehab</td>
<td>’Omics sequencing and techniques</td>
<td>’Omics sequencing and techniques</td>
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Prevention

Detecting risk of opioid misuse

**Problem:** Opioid-based medications are often prescribed to manage pain, both in acute care settings and for chronic conditions. However, the addictive nature of these medications for some patients can cause considerable health and social harm. The challenge is identifying these patients at risk of problematic use while maintaining access to those people requiring opioids for pain management.
**Solution:** AI techniques may be used to predict potentially problematic use of opioids and to identify patients at the highest risk of overdose. Studies have used machine learning techniques to examine factors associated with opioid misuse and overdose occurrence [29,30]. Additionally, natural language processing has been used with unstructured EMR data to develop an automated assessment tool of opioid misuse risk [31].

**Automatic recognition of diabetic complications**

**Problem:** Diabetes is associated with a range of serious health complications including a number of conditions that affect eye sight and can cause blindness if left untreated. Ensuring these conditions are identified as early as possible is important to prevent irreversible damage.

**Solution:** A study conducted by Google used deep learning to create an algorithm for automated detection of diabetic retinopathy and diabetic macular oedema in retinal fundus photographs. The learning model is based on a collection of photographs already rated by physicians. The study authors note potential advantages of an automated system including consistency of interpretation (because a machine will make the same prediction on a specific image every time), high sensitivity and specificity and near instantaneous reporting of results. This method has not yet applied in clinical practice and needs further assessment to compare outcomes of an automated approach with current ophthalmologist practice [32].

**Supporting wellbeing using IOT**

**Problem:** Preventing chronic conditions involves attention to diet, physical activity and a range of other lifestyle factors. In today’s environment where many people lead sedentary lives and are surrounded by calorie-dense food options, it can be difficult to make and sustain healthy choices.

**Solution:** Springday is an Australian company that enables users to embark on their wellbeing journey. Users identify a starting point, set goals and receive personalised guidance and lifestyle content. Springdale sources and collates wellbeing experts, learning modules, wearable technology integrations, and motivational and communication tools and connects them into a customisable and user-friendly experience, available via a web portal and mobile application. Users participate in company-wide and individual initiatives such as challenges, self-paced programs, face-to-face health services and community events. Springday aggregates, and reports on, platform usage and behaviour change metrics in a real-time dashboard [33].
Treatment

Managing Type 2 Diabetes using integrated digital technology

**Problem:** Many people with diabetes need to regularly monitor glucose levels. This information should be collected and stored to monitor trends over time. Additionally, if a health risk is identified, health professionals should be informed in real time.

**Solution:** GlucoMe is a digital diabetes technology that uses IOT devices to support both patients and medical professionals in diabetes management. Blood glucose measurements and insulin intake are automatically recorded by the GlucoMe Smart Glucose Monitor and Insulin Pen Monitor. The data are transferred to each patient’s smartphone, stored in the GlucoMe Mobile App, and analysed in a cloud-based Digital Diabetes Clinic. The Digital Diabetes Clinic platform generates personalised reports and real-time alerts. Using machine learning, the platform also recommends proactive treatment approaches that are considered by the patient’s medical professional [34]. This solution is being used systematically to provide a home-care program for diabetes in India, a country with a high prevalence of diabetes [35].

Personalising cancer treatment

**Problem:** Cancer is a complex condition that often require treatments from multiple health care providers. Sharing information between providers can be challenging and many patients need to repeat their “story” and carry files between appointments. Additionally, a cancer diagnosis can often cause drastic changes in a person’s life affecting their ability to work and maintain a routine with flow-on effects to a person’s mental health and psychological wellbeing.

**Solution:** Beyond is an online cancer community that connects patients, physicians and cancer survivors. Patients using the app are provided with an online repository to organise, and securely manage documents on their mobile device, connect with a network of cancer survivors and access leading clinicians who answer patient questions. Beyond uses AI techniques to provide personalised information and notifications and also has a clinical trial matching service. The data collected via the Beyond platform has been used in a number of published research studies relating to cancer-related fatigue and the patient journey and treatment lines for metastatic pancreatic cancer [36].
Integrating ‘Omics for targeting drug therapy

**Problem:** Many diseases do not have a single cause but instead develop due to a complex interaction between genes, biology and the environment. There is still much that is not known about the biology of disease. Advances in our understanding of disease and gene associations and the cellular mechanisms of disease will likely need a combination of GWAS, PheWAS and metabolomic analysis.

**Solution:** Advances in ‘Omics technologies provides opportunities for increasing our understanding of the underlying causes of diseases and identifying genomic, phenotypic and metabolomic contributors. The following examples highlight how GWAS, PheWAS and metabolomic analysis have been used in research for specific diseases but researchers predict that in the future, advances in our biologic understanding of disease will depend on combining approaches to better understand genotype, phenotype and metabolites.

GWAS of drugs such as statin, clopidogrel, and interferon-alpha effects have shown that variability in drug response is ancestry-dependent due to the vast difference in distribution of specific genetic variants across populations [26].

A PheWAS conducted using both genetic and self-reported health history data from the 23 and Me database investigated the phenotypic traits associated with particular gene variants (T helper (Th) 17 cells that produce the cytokine interleukin 17 (IL-17)) known to play a role in multiple autoimmune and infectious diseases. The results of the PheWAS replicated known associations for autoimmune traits (important as data was self-reported) but also produced novel associations with phenotypic traits such as increased risk of tonsillectomy, strep throat and teenage acne [37].

In the area of metabolomics, paediatric studies have evaluated cerebrospinal fluid of children with influenza-associated encephalopathy to identify biomarkers that may lead to earlier diagnosis. Additionally, metabolomics analysis has been used to distinguish different degrees of inflammation in cystic fibrosis [15].
Maintenance

Ensuring people with dementia can live safely in the community

**Problem:** People with dementia and their carers may need additional support to live safely in the community. As the disease can affect memory and mood, ensuring that a person with dementia undertakes routine activities to maintain health such as medication, physical activity and personal hygiene is important for their care team to monitor.

**Solution:** A trial funded by England’s Department of Health has been established using environmental sensors to set up automatic monitoring systems to support health care professionals to assist patients with dementia and their carers. The aim of the trial is to provide earlier indication of patient needs and allow the care team to provide a more timely response. Passive sensors are embedded in a patient’s home to monitor the environment and use of appliances [38,39]. Innovations include smart wallets that monitor medication compliance by measuring how many pills have been removed from a blister pack. Medical devices and wearables track physiological parameters (such as blood pressure) and transmit information via Bluetooth and Wifi. The data collected are processed using machine learning algorithms to learn the patient’s daily patterns and find possible pattern deviations, detect if patients are agitated or irritated, and detect the possibility of urinary tract infections (a common health issue) [40]. Similar monitoring technology, Sofihub, providing passive monitoring and intelligent messaging has been developed in Australia and commercialised [41].

Remote delivery of cardiac rehabilitation

**Problem:** Following a cardiac event, such as a heart attack, rehabilitation services are required to support a patient to regain strength and mobility to resume activities of daily living. For many patients, particularly those that live in rural and remote areas, it is not practical or convenient to receive all their rehabilitation delivery in face-to-face consultations.

**Solution:** Cardihab’s Digital Cardiac Rehabilitation provides a smartphone app for the patient and a clinician portal that complements traditional, face-to-face delivery while also supporting a new, scientifically validated remote delivery model [42]. The solution is being used by health services in New South Wales and Queensland with a clinical trial of the approach conducted in Queensland with involvement from Australia’s national science research organisation, CSIRO [43]. The trial found that a smartphone-based home care cardiac rehabilitation program improved rehabilitation uptake, adherence and completion for patients who had suffered a myocardial infarction. The home-based
program was as effective in improving physiological and psychological health outcomes as traditional cardiac rehabilitation [44].
Section 6: Conclusion

In this paper, we have discussed opportunities to combine technological advances in data collection and analysis, artificial intelligence and genomics with new and existing data sources that can improve the planning and delivery of health services across the care continuum from prevention and health promotion to treatment and maintenance.

While the future of technology in health care is exciting, new technologies and techniques will not replace the need for human health professionals but may considerably change their role with the requirement for new skills in data analysis and interpretation. Additionally, change that results from the applications of these technologies will be incremental. As the examples in this paper demonstrate, some areas of health care and specific diseases such as cancer, have received more attention than others and advances in personalised treatment are progressing rapidly. We must ensure that these advances are shared across the health sector to reduce health inequalities and health inequities.

Finally, this paper highlights some of the many areas in digital health that further research is needed. In Australia, the Digital Health Co-operative Research Centre (DHCRC), was launched in 2018, and is a major research, development and translation program trying to facilitate governments, industry, and research to work together to realise the potential of data and digital technologies in supporting the health of all Australians.

The DHCRC is a 7-year national and international collaboration between 64 health and technology organisations, and 16 universities focused on enhancing the deployment and use of information technology, all forms of data and computable knowledge to drive improvements in the wellness and healthcare of all citizens, efficiencies in the health system and the growth of health and medical technology companies.

The DHCRC works closely with Australian Digital Health Agency, with the goal of contributing to the achievement of its ‘National Digital Health Strategy’, particularly its goals to give consumers more control of their healthcare decisions and promote Australia’s global leadership in digital health and innovation.

The DHCRC will also contribute to the achievement of a range of growth priorities of the medical technologies and pharmacy sector. The DHCRC’s industry partner base covers public and private
health organisations across all Australian jurisdictions. This coverage is indicative of the recognition of the transformational potential of digital health and their commitment to substantively contribute to unlocking this potential. Through this coverage, the DHCRC has the capacity to positively impact every Australian.

The DHCRC plans to achieve national impact through four interlocking research programs:

1. Information capture, storage and flow
2. Identifying and managing health risk
3. Improve value, quality and safety through intelligent decision support

The research areas are planned to be spread across a variety of care settings that include:

- Home and Work
- Acute and Primary
- Residential aged care
- Rural and remote
- Rehabilitation.
References


