The Dangers of Patient Data in Clinical Decision Making

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Personal tracking devices may hold information crucial for diagnosing illnesses. However, what are the consequences of cognitive bias on interpretting these data in order to inform clinical decisions? A literature review is conducted in order to identify potential potential risks and consequences.

Health and Wellbeing Data

The explosion of social networking websites, mobile apps and consumer devices for tracking personal information has created detailed data sources about health and wellbeing. These data have been demonstrated to **promote positive health behaviours**, such as encouraging healthy diet [1] and assisting cancer recovery [2].

These benefits have led calls to investigate using consumer technology within **healthcare** to support clinical decision making, in turn leading to more accurate diagnoses, improved patient outcomes and reduced mortality [3].

Dangers in Clinical Practice

Research over the last 50 years has revealed a number of **cognitive biases** which negatively affect decision making [4]. This particularly pertains to clinical decision making, where bias can lead to misdiagnoses and higher mortality. It has been established that cognitive bias is a major cause of preventable diagnostic error, but extremely challenging to study and reduce [5].

The introduction of health and wellbeing data may **introduce biases** related to data interpretation, thus could lead to further bias and higher mortality.

Methodology

The disciplines involved in this research include Health Science, Cognitive Science and Computer Science. This project opted for a **Web Science** approach, an interdisciplinary perspective which focuses on the Web as a common factor.

To establish a list of relevant biases and their effects, a **literature review** was conducted. First, biases which affect clinical decision were drawn from the work of Croskerry [5]. Then, interpretation biases were identified from work in Cognitive Science. Finally, the biases were taxonomised, providing five types of bias.

What's tracking our lives?

Facebook status updates, location, social groups

Jawbone sleep, steps taken, mood, diet

Moves walking, running, cycling, vehicle use, location

Apple Watch heart rate, steps, calories, excersise, standing

Results

The literature review found that introducing patient data in clinical scenarios adds **additional bias** to clinical decision making.

It has thus been established that there are **significant negative effects** of bias in using data from commercial devices in clinical decision making. The types of bias identified are explained below.

Conclusions and Future

Health and wellbeing data may lead to more accurate diagnoses, but biases may lead to poor decisions and missed diagnoses. This research has revealed some of these potential biases.

I will draw from this for my PhD, conducting experiments to demonstrate the effect of bias. The aim is **raise consciousness** to the dangers of using data from consumer technology.

References

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False pattern recognition

In uncertainty, clinicians are more likely to observe patterns in data, using them without consideration of the statistical significance.

Example A person who suffered a recent loss, is drunk and admitted to A&E by a friend out of fears for their safety. A nurse scans the individuals phone (which has a location tracker), revealing daily visits to a bar. The nurse diagnoses alcohol dependence and recommends support groups.

Assessment Misdiagnosis of alcohol dependence. The nurse did not know that the patient rarely drinks, and is employed at the bar.

Positive tendancy

Clinicians are more likely to choose options that seem favourable, in spite of unknown probabilities of outcomes.

Example Patient presents at GP complaining of weight gain. They use an app to record dietary intake. The clinician sees, in red text, that the patient's calorie targets are being consistently exceeded. GP advises adopting a healthier diet.

Assessment Missed diagnosis of Cushing's syndrome. The patient's intake was in fact lower than the NHS's recommended calorie intake. The diet was deemed poor due the negative way data was presented.

Misuse of prior knowledge

In cases of constrained time or resources, clinicians may use prior knowledge without consideration of its reliability or relevance.

Example Patient walks into A&E complaining of chest pain. Concerned that they are experiencing an asthma attack, they present an app showing inhaler use during previous chest pains. The patient is diagnosed with an asthma complication and given preventative medicine.

Assessment Diagnosis of indigestion was missed. Nurse was primed with data about asthma, leading to an incorrect diagnosis.

Poor communication

When there is little available knowledge about a patient, clinicians are more likely to communicate ineffectively.

Example A sprinter is experiencing severe knee pain. The nurse asks if their activity tracker records information about gait (limb movement). Unfamiliar with the term, the patient responds "no". Lacking data, the nurse recommends rest with painkillers.

Assessment Missed diagnosis of Patellar Tendonitis. The tracker *did* record data about gait. The patient could have provided this had less technical terminology been used.

Specialisation

Clinicians may neglect base-rates, over-willingly accept one's own beliefs, and be unable to use tools atypically.

Example Patient with a toothache sees a dentist. Their toothbrush tracks brushing technique. Familiar with the device, the dentist checks the most recent technique and finds it is poor. Dentist diagnoses abscess and recommends painkillers.

Assessment Misdiagnosis. Frequent typical use of the toothbrush data led the dentist to not check earlier data, which would have revealed good brushing technique and the most recent brush an anomaly.

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