The Dangers of the Quantified Self in Clinical Decisions

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Abstract

The increasing ubiquity of personal tracking devices is leading to calls to use Quantified Self data to support clinical decisions. Such data has been demonstrated as promoting positive health behaviours, such as maintaining a healthy diet. However, clinicians' method of practice is grounded within data-impoverished environments, characterised by tight time and resource constraints. Within such environments, humans are subject to cognitive bias and poor judgement when making decisions, which may lead to undesirable outcomes when interpreting data. Through reviewing literature on decision making within constraints, this workshop paper identifies four undesirable outcomes pertaining to the use of Quantified Self data in clinical decisions: favouring illusory patterns, positive tendency, misuse of prior knowledge and technological limitations. Future research will focus on studying how and when these outcomes present within clinical settings.

Author Keywords

Quantified Self; Clinical Research; Decision Making

ACM Classification Keywords

H.5.2 [Information interfaces and presentation (e.g., HCI)]: User-centered design.; J.3 [Life and medical sciences]: Health

Introduction

The explosion of social networking websites, mobile apps and consumer devices for tracking personal information has created new detailed data sources about individuals. The pervasiveness of these technologies allows the capturing of extremely detailed data about health and wellbeing. Coined the "Quantified Self", this information has been demonstrated to promote positive health behaviours, such as reducing stress and improving communication during the recovery of cancer patients [7].

The health benefits of the Quantified Self have led calls to integrate consumer technology within healthcare. In the UK, the recent Personalised Health and Care 2020 framework proposes that health and wellbeing data, including data from wearable devices and mobile health apps, will form part of patient health records by 2018 [10]. The framework proposes that clinicians will be able to use this data to make better decisions, in turn improving healthcare, reducing costs and empowering patients to make their own decisions. It has been proposed that the Quantified Self can contribute to preventative medicine, helping clinicians track the lifestyle choices, environmental factors and general wellbeing of patients in order to avoid health problems [14]. Initial implementation of this is evident in the USA, with the Food and Drug Administration's approval of several consumer tracking devices for clinical trials, citing the importance of quantifiable analysis of physical activity to physiological monitoring [15].

However, while Quantified Self has been demonstrated to promote positive health behaviour, there has been little research on how the presence of such data may affect decisions within clinical environments. The introduction of such data to clinical environments without a deep understanding of potential dangers may lead to adverse effects, such as misdiagnoses or harmful outcomes (such as death). The Personalised Health and Care 2020 framework briefly raises this risk: "the failure to use information properly in health and care means people can experience unnecessary levels of preventable ill health" [10]. However, the framework gives no detail on how information should be used and how problems may be mitigated. It is not yet clear what undesirable outcomes may be present when introducing Quantified Self data to clinical decisions.

Decision Making with Data

It is now widely accepted that there are two forms of decision making: System 1 and System 2 [8]. System 1 decisions are made quickly and automatically. In contrast, System 2 decisions are made slowly and deliberately. The automatic nature of System 1 decisions is from a lack of conscious reasoning; instead, a number of heuristics and cognitive biases are relied on to make a decision more quickly. While heuristics and biases may deliver an optimal solution most of the time, the results may sometimes be undesirable. Hence, System 1 decisions often result in error [8].

Within clinical environments, particularly Emergency Rooms, time is tightly constrained and decisions must be made quickly [4]. These decisions are typically characterised as System 1 decisions. It has been established that a wide variety of cognitive biases are prevalent in clinical decision making, which may lead to poor judgement and errors [4]. While there is ongoing research around biases within clinical decisions, there is little research in how the provision of data affects bias [3].

Due to its pervasive nature, Quantified Self data varies significantly in structure, context and content, making it difficult to study how it is interpreted. It has been established that data which is difficult to interpret or poorly structured leads to poor judgement and decision making [11]. It has also been established that large amounts of data may lead to data overload, a situation which may lead to undesirable techniques for interpreting data [9]. This is exacerbated by time constraints, as has been observed within Intensive Care Units, where false positives were frequently identified [9].

Characterizing Undesirable Outcomes

Based on research and experiments around heuristics and cognitive bias, four undesirable outcomes have been identified: *favouring illusory patterns*, *positive tendency*, *misuse of prior knowledge* and *technological limitations*. Each outcome is expanded on below, with the characteristics and consequences discussed.

Favouring Illusory Patterns

When there are time constraints, constraints on how data may be controlled, or it is not clear how data should be used, there is an increased likeliness of illusory patterns being identified [17]. Illusory patterns are seemingly meaningful relationships in random data which, despite their statistical insignificant, may be used to influence a decision [8]. Quantified Self data is specific to individual patients. It has been found that clinicians neglect other sources of data, for example base rates of a particular disease, when presented with information specific to a patient [2]. Illusory patterns found on such data may therefore be considered more important than other sources of information. This is an example of the representativeness heuristic, where the statistical significance of an observation has little influence on its importance in reasoning [8].

Illusory patterns may thus lead to neglecting other sources of information, such as base rate, patient presentation or a patient's health record. In turn, this may lead to misdiagnoses, rationalising unusual diseases, overutilisation of resources, and contribute to inaccurate estimates of base rates [3].

Positive Tendency

Decisions are often influenced by current emotion and desire for a good outcome. This is known as the affect heuristic [8]. It has been found that people heavily rely on affect in time-pressured and high risk situations [5]. Thus, a clinician's emotional state can significantly affect their interpretation of patient data and their decisions.

The affect heuristic leads to data being interpreted in ways to support one's own desires [12]. Subsequent findings will be prone to confirmation bias, where findings are emphasised based on if they support one's own desires or beliefs [8]. Within situations in which variables are unknown, it has been found that people are less willing to eliminate an original hypothesis, with a person attributing unjustified rationality to that hypothesis [16].

Subsequently, data may be interpreted in ways impacted by emotion. Personal hopes and regrets influence decision making, which reduces objectivity. Clinicians may make diagnoses based on what they hope to find, leading to the preservation of weak hypotheses and diagnoses, despite evidence to the contrary. In turn, this may lead to errors and adverse events including incorrect and missed diagnoses [3].

Misuse of prior knowledge

It has been observed that decisions are likely to be influenced by prior experiences [13]. This effect is known as priming, and is of particular importance to clinical

Table 1: Design rules to mitigate undesirable outcomes.

Favouring illusory patterns
1. allow comparison of data sources, e.g. overlaying national trend data over an individual's data 2. provide greater control over data 3. provide tools to validate patterns
Positive tendency
1. aid in challenging hypotheses by providing greater control over data 2. designing for rapid usage to allow more time for considering of hypotheses
Misuse of prior knowledge
1. allow comparison to base rates to avoid comparison to prior patients
Technological limitation
1. intuitive UI design to allow flexible use of tools (e.g. visual programming languages) 2. designing for rapid usage to allow more time for considering other uses of tool

settings as clinicians see many patients. Exposure to one piece of information influences how another piece of information is perceived [8].

There are two crucial cases where this is a concern: priming between patients, and priming between patient data sets [3]. The former pertains to a clinicians decision on one patient priming a decision for another patient. The latter pertains to a clinicians interpretation of one piece of information priming how another piece of information is interpreted. Past experiences of using data will inform what is being looked for in data. This is an instance of the framing effect, where the way in which a problem is presented affects the outcome of a task [8].

Earlier decisions or interpretations may therefore affect the performance of later decisions or interpretations. A clinician may base their diagnoses on the perceived likelihood of a particular disease, which may be influenced by what the clinician has observed previously, which may result in an incorrect diagnoses [3].

Technological limitations
Limitations of tools or analysis techniques may lead to a relying on known examples, which may limit insights which may be gained from data [1]. Clinicians may be limited to using a data source for a purpose that they've successfully used it for before, despite other uses being possible. Problem solving has been demonstrably less effective when a solution requires atypical use of an object [6].

Information which is considered more important, such as recent information, is judged more frequent and therefore more heavily relied upon for decision making [8]. When interpreting data, the availability heuristic causes some pieces of information to become disproportionately relied upon based on inaccurate estimates of frequencies.

Having limited time and resources leads to focus on the little available information [3], thus leading to a more subjective decision.

This limits the capability of a clinician to gain insight from patient data, leading to less informed decisions. It can lead to missing a diagnosis due to inability to interrogate data in an unusual way [3].

Conclusion and Future Work

This research has thus far aimed to identify undesirable outcomes of introducing Quantified Self data to clinical decisions. Four have been identified, which are summarised in Table 2 along with their characteristics and clinical consequences. While this is not an exhaustive list, this preliminary work suggests that there are questions that should be raised before introducing Quantified Self to clinical decisions. Namely, what are the undesirable outcomes, how do they manifest themselves, and how can they be mitigated?

The nature of Quantified Self data plays a large role in each of the outcomes. As such, there may be a number of design rules which could mitigate these outcomes, including in user interface design and data visualisation. Table 1 gives a few initial suggestions of such rules.

This research proposes that the introduction of data may lead to certain dangers relating to the nature of decision making and biases. Future work will involve further investigation in order to identify the nature of these dangers. This research aims to raise awareness of undesirable outcomes of cognitive and interpretative error, informing both clinical training and how Quantified Self tools and devices are designed.

Table 2: Possible undesirable outcomes, their characteristics and consequences

Outcome	Characteristics	Consequences
Favouring illusory patterns	Illusory patterns will be considered more significant than other data sources due to the representativeness heuristic.	Neglect of base rates and other sources of information. May lead to misdiagnoses, overutilisation of resources and contribute to inaccurate estimates of base rates.
Positive tendency	Current emotion leads to forming particular hypotheses for data interpretation (affect heuristic) which leads to confirmation bias.	Interpretation of data informed by current emotions, reducing objectivity of diagnoses, potentially leading to incorrect diagnoses.
Misuse of prior knowledge	Prior experiences with data from other patients may lead to data of current patient being interpreted in a particular way (priming and framing effect).	Prior experiences lead to neglect of base rates and limited interpretation of data sources of current patient, possibly leading to inaccurate diagnoses.
Technological limitation	The limitation of the tools or techniques (functional fixedness) leads to clinicians utilising only ways they have used or seen previously (availability).	Clinician may miss important insights from the data and miss a diagnosis.

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