The Quantified Patient in the Doctor's Office: Challenges in Designing for Clinical Decision-Making Settings

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ABSTRACT

While the *Quantified Self* movement has largely centred around the individuals own use of his or her data, the same kinds of patient-captured information about their well-being could, in theory, facilitate more accurate and effective medical diagnosis and treatment. In practice, however, introducing such data during in a way that they can be used effectively and without additional risk during patient visits and hospital episodes creates significant challenges, that we believe, HCI research can help. In this paper, we seek to understand the primary bottlenecks to the use of QS data during patient visits in both primary and secondar (specialist) care through a literature survey and group

Author Keywords

Quantified Self; mHealth; Clinical Decision-Making

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INTRODUCTION

Empowering patients "take charge" of their health is an idea frequently championed by politicians [**?**, **?**], technologists [**?**], journalists [**?**] and healthcare experts alike [32]. Yet, despite countless government and industry-led initiatives across Europe, the UK, and North America, to inspire this "patient-led healthcare revolution", it has yet to happen.

One area, however, where individuals have been taking the lead in trying to understand their own health, is the *Quantified Self* movement [], primarily comprised of hobbyists and non-health experts who use technological tools to meticulously record and interrogate the minutiae of their physical and mental states over time. As the population of those interested in self-tracking grew and attracted mainstream interest, the industry has swiftly responded to the expanding demand for self-tracking tools and technologies with a now enormous collection of wearable and embeddable sensors. These technologies now enable people to record and keep track of aspects of their health with less effort and better fidelity than ever previously, and will continue to improve such as by being less invasive, more comfortable, and more accurate.

While the direct application of such sensors to understanding patients' particular symptoms, situations and lifestyles in the healthcare context would seem straightforward, most physicians today avoid or outright reject the use of self-logged QS data. Even when this information is provided by patients and is reference, it is still rarely, if ever, used for differential diagnosis.

What are the barriers to the use of self-logged QS data in critical clinical decision making settings? This is a delicate question to approach for several reasons; first, during the a course of a single patient visit, there may be many kinds of decisions made by a plurality of medical professionals in different roles, in similarly diverse settings. Paramedics in an ambulance, triage nurses within an emergency room, specialists in a acute care unit or hospital wards, to general practitioners (GPs) in their surgeries, all make decisions regarding a patient under very distinct situational and informational constraints [**?**]. Second, even if focus is centred around a single setting, by a single class of medical professionals, such as GP surgeries, there may be significant disparities in the ways different GPs do things; for example, the degree to which GPs use electronic medical records (EMRs) [**?**] to organise patient data, prescribe particular tests or treatments [], or the mechanism and method that they use to maintain good patient relationships [] can be highly inconsistent. Finally, clinical decision making is a field that is not only long established, but one of the most specialised occupations in the modern workforce; therefore, understanding the effects of the introduction of any new information into such a setting requires an in-depth understanding of the processes, training and tradition.

For our investigation, we focused on two different roles: primary care physicians on the "frontline" of the medical service, and secondary care specialists who work in hospitals in specialised units. In our investigation, we sought to understand the fundamental nature of the barriers to adoption of broadly-classed 'self-logged' patient data, particularly of the most common types facilitated by the many kinds of consumer health monitoring tools becoming available. That is, we wished to identify whether reasons that such self-logged data were still, so often, deemed useless by clinical professionals, included *what* was captured, how it was captured, the

1. *Data subject*: Lack of relevance or utility of *what* is captured

2. *Sampling method*: Problems with *how* and *when* information is captured

3. *Accuracy*: Lack of trust in accuracy of instruments or capture method

4. *Access*: Problems with physician *access* to the data

5. *Patient communication*: Interference with patient clinician communication

6. *Workflow*: Interference or exclusion from diagnostic workflow

7. *Biases*: Danger of cognitive biases introduced by data?

8. *Other*: External factors? (*data handling*, *legal*, *billing* etc)

Figure 1. Initial dimensions for categorising barriers to clinical use of self-logged/QS data.

ways in which it was represented or made available during a patient consultation, or due to other, yet unidentified problems derived from looking at or processes required to derive insight from it. From this, we wished to extrapolate how such problems might help be shaping and solved through HCI research, such as by re-thinking tools people used to monitor themselves, the kinds of data they captured, or the ways that physicians and medical professionals might access and use it, towards the visions of eHealth and mHealth set out so often in the popular press (e.g. [**?**, **?**, **?**]).

OVERVIEW OF APPROACH

We began with an initial set of broad dimensions (Figure 1) chosen to represent the potentially many kinds of reasons that self-logged, QS data remains far from fulfilling its potential in clinical practice.

Since these dimensions encompassed a broad set of possible factors, including data-oriented problems (such as pertaining to subject, quality and sampling), situational constraints, and practice constraints, we wished to understand which, if any, of these dimensions had support from previous studies. This lead us a broad survey of medical literature, which we describe in the next section.

Then, to investigate whether we could gather primary evidence towards the importance of any of these dimensions, we followed with a role-play study in which practicing GPs and specialists were presented with patient illness scripts, based on real cases, in which patients brought various QS data with them while in the process of presenting their complaint. We asked GPs and specialists to come up with their own diagnosis, following a think-aloud protocol. We then transcribed, annotated and derived codes from each session to identify reasons the QS data were or were not consulted, and ways that the presence of the QS data influenced the diagnostic process. From these codes, we derived a set of themes, which we then used to compare our findings to previous findings in the literature. Finally, we discuss the limitations of our study and future work.

BACKGROUND

We contextualise our investigation against two closely related fields: the first, *evidence based medicine* sought to expand the use of empirical methods (such as used in epidemiology) for evaluating and improving the effectiveness of decisions such as those affecting treatment choices. The second, *clinical decision making* examines the cognitive, interactional and situational processes which influence how practitioners arrive at decisions, under the practical constraints necessary for conducting their practices. In this section, we first introduce at a high level, common visions of how technology-enabled, patient data-driven healthcare might be realised in the future. We then discuss evidence-based medicine and the role of clinical decision making literature to our investigation.

Visions for Data-driven eHealth / mHealth

Notions of "big data" and "data driven healthcare" have inspired many visions for more data-informed healthcare internationally. In the popular press, Thomas Goetz's *The Decision Tree* outlined a vision in which every person will be DNA-tested at birth, and tracked with sensors throughout their lives; the resulting piles of data would be used to classify and compute (through statistical measures) optimal treatments and actions. Policy makers have set out national agendas towards such a goal; the UK's Personalised Health and Care 2020 framework set out a vision in which health and well-being data, sensed from wearable and environmental sensors, would seamlessly integrate with patient health records by 2018 [**?**]. The framework proposes that these data would "fill in the gaps" between visits with their GP or specialist, enabling clinicians to more effectively perform personalised differential diagnosis at point of care. It is anticipated that the introduction of such technologies will simultaneously improve outcomes substantially and drive down costs. Other visions include use in preventative medicine, to enable early onset detection of chronic conditions, thereby potentially reversing the course of conditions before they set in [31]. Exploratory data mining of sensed data is also likely to radically improve our understanding of both prominent and rare medical conditions, by revealing relationships among genetic, lifestyle, and environmental factors that might contribute to patients' symptoms. Initial enthusiasm for this vision is also evident in the US, with the US Food and Drug Administration's approval of consumer tracking devices for clinical trials, citing the importance of quantifiable analysis of physical activity to physiological monitoring [35].

Responding to this interest, the race to attract end-user consumers to better and more accurate physiological sensors has taken off past 8 years. New, freshly funded companies such as Withings, FitBit and Jawbone, have been joined veteran sport performance monitoring device makers such as Garmin, while established brands for sport to consumer electronics, such Nike and Sony have joined the fray to each develop attractive wearable personal tracking devices. While still a minority, several, namely at the time of writing iHealth and Withings, have had several of their consumer-level sensors

certified for clinical use, as under the US FDA Class-1 and 2 medical device classification scheme.

Evidence Based Medicine: Clinical Decision-Making with Data under Uncertainty

The term *evidence-based medicine* refers to the use of epidemiological methods in both patient-level decision making and formulation of population-level clinical care guidelines. In the first use of the term, David M. Eddy pointed out that, while outcome analysis may make it seem that there is a clear path towards achieving more accurate, or at least consistent, diagnoses, things are never that simple in practice [14]:

> Decisions might be variable but they are not whimsical or flippant. The variability occurs because physicians must make decisions about phenomenally complex problems, under very difficult circumstances, with very little support. They are in the impossible position of not knowing the outcomes of different actions, but having to act anyway.

Eddy, thus, argues that, that due to the nature of the complexities of assessing individual patients' conditions under the constraints in place, care targets and practice recommendations alone will not achieve better health outcome. Instead, working under extreme uncertainty is a necessity and should be embraced with the acknowledgement of the effects of various decision-making constraints and biases that are known to exist.

Clinical Decision-Making

Clinical decision-making biases have long been studied in the medical community. Modern texts for nursing and clinical evaluation have formalised the diagnostic process of determining a patient's disease or condition based on available evidence, including presenting symptoms as a technique known as *differential diagnosis* [33]. This is usually described as some variation of the following procedure: First, the physician gathers all information available about the patient, creating a list of the patient's symptoms. Then, she or he lists all possible candidate conditions for the symptoms, which is then prioritised with most the urgently dangerous possible causes first. Finally, possible causes are ruled out or treated systematically.

Cognitive Dispositions to Respond

Recent research has revealed that clinical decision-making is often strongly influenced by cognitive bias, leading to preventable adverse events, worsened patient outcomes, and higher mortality. Croskerry et al. characterised a [11]. [20] states that cognitive bias is a major cause of preventable diagnostic error, but is extremely challenging to study and reduce. This complements earlier discoveries by [23], in which people tend to use biases when making decisions under uncertainty, occasionally leading to severe errors. Many forms of cognitive bias have been identified – Wikipedia lists over 350[1] – however, the consequences of biases in clinical decision making remain largely unexplored [11]. It is thus unknown how the provision of patient data may affect bias in clinical decisions.

PRE-STUDY: LITERATURE REVIEW

We anticipated that the slow uptake of the use of self-logged QS could potentially be attributed to a large number of factors, and thus decided it prudent to first do a survey of medical, quantified-self and HCI literature. Our objective was to establish a theoretical framework from which we could then identify areas that could require further investigation, as well as opportunities where research in HCI could potentially help.

Literature Review: Method

We started with a set of search terms broad enough to encompass studies of clinical practice where patient-logged data (both paper-based and digital, manual and automatic) were introduced into a clinical setting. To do this we searched PubMed, Google Scholar and the ACM DL for keywords "patient diaries", "care diaries", "wellbeing diaries", "self-report diaries", "quantified-self", "smartphone apps", and "wearable sensors".

Since we wanted to focus on the usage of data by medical experts, we excluded studies about use by patients themselves, such as for feedback, reflection, goal setting and self monitoring, including behaviour-change studies and studies of motivation to self-diaries, which were prevalent from the HCI community. Focusing only on existing practice, we omitted papers describing new interfaces and systems that have not had substantial adoption. We also excluded papers discussing the capture side of health diarising and life-logging by patients, except where aspects of capture affected its later use. We were careful to include papers that discussed any issues relating to the use of patient data in clinical setting, including those that discussed human factors issues specifically, to more broadly theatres and emergency rooms.

After finding a small set of results, we then broadened our search to include studies that discussed the use of patient data in medical decision-making, including both patient-supplied and clinical data held by providers themselves. We included "telemonitoring", and "electronic patient records". This hoped to find a broad range of factors spanning human-factors issues to social, cultural, institutional, situational, among others.

For each paper, we identified problem(s) in the clinical use of data, which were first added to a spreadsheet and linked to their original source. After examining each of the papers, 2 researchers organised the list into themes, attempting to merge all problems with the same underlying cause, while keeping those that did not overlap distinct. During this process, we identified a set of themes related specifically to cognitive biases, which we analysed and report separately below.

Excluded papers relating to self-recorded data which patients were asked to record by their physicians, such as papers containing the words "telemonitoring" or "telemedicine". Literature reviews were excluded.

Literature Review: Results

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[1]Wikipedia – List of cognitive biases – **http://en.wikipedia.org/wiki/List_of_cognitive_biases** [Accessed 4th Sep 2014]

From an initial set of 2340 results, we identified 429 papers that actually contained at least one of the search terms among keywords and the abstract. From here, we identified *XX* relevant papers according to the criteria defined above. From this we derived the *CC* themes visible in **??**, omitting themes pertaining to cognitive dispositions to respond which we discuss next.

High-level Themes
Implications from bias

METHODOLOGY
May - June 2015

Inspired by methodology from other research

A focus group and two interviews were conducted

Recognise the value of self-logged data

Recruitment

Analysis
Two interviews

One focus group

RESULTS
Participants in the focus group - seven specialists in the US (six male) and three NHS GPs in the UK.

Reorganising information into a medical history Five hospital specialists (S1, S2, S3, S4, S5) stated that they needed to reorganise the information that was given to them in the form of a medical case. In particular, they wanted a more complete history so they could understand how the patients current even fits within a timeline, or whether its a distinct event. GP1 said he needed more specific information about his medication, rather than just a couple of blood thinners. for me, there's an incomplete history here. So, you know, the first place I would go is back to the patient, and try to pull out, what are the details of the timeline really, the timeline. Is this a distinct event or are this linked somehow, and pull it out from her, the history. S2 I knew this wasn't a regular medical history. so right away I knew this was just like a New York Times case that you see in the times magazine, so it made me think this is like an oddball thing, it's not just a typical case, we're looking for oddball things, and so reading this, though, trying to approach it like we would in an office, really just looking for things that are more serious, like trying to see what's the worst possible thing that she could have, approaching it that way S5

Particularly prominent within the session with hospital doctors was the need to reorganise the scenario that aligns and supports their work routines. One hospital specialist explained that it was difficult for them to follow the medical case in the scenarios because they did not provide the patients structured medical record which would give greater detail into the patients history and flow of interventions in a standard format. this has been going on for a longer period of time and then I got the sense that it started 18 months ago but you know, I would like the confirm that. [...] Was that when it really started? Or is there, in this pattern, you know, along the lines of is this real pathology is this been this pattern of it going on and frequent doctor visits and nothing found, uhm, you know its just anything more has she had recent blood work has she had recent x-rays or tests that might tell us that there's real pathology or that there's something to focus in on uhm you know, those kinds of things. S3

Because there was no patient, some clinicians role-played the patient: She's a student, third year probably coming up to exams. Is it a tension headache? GP1 She's a student, I suppose I'm already thinking alcohol psychology. GP2 Evaluating the data quality and completeness Concerning the heart rate chart, GP1 stated that he would need to understand how the patient recorded that data. One important factor raised was the need to understand if any illness or medication had interacted which may contribute to a change in the patients heart rate. GP2 and S2 also mentioned he would need to understand what the patient was doing at the recorded times, particularly during the high peaks. In addition, S2 needed to know what symptoms the patient was experiencing at those times.

The heart rate chart also provoked comments on the reliability of the data, relating to both the accuracy of the recording equipment and how the patient recorded the data. GP1 explained that he could not assume that the data was objective enough, and that spot checking wasnt enough - he would instead need a trace. He felt he would need to take measurements using his own calibrated equipment, which he could trust: I want to use my machine, which has been precalibrated, not off the shelf, because I don't know about this machine's calibration. Can I trust all the data? No. Can I assume all the data is correct? No. So I have to use a calibrated machine which I feel happy with, that I've used before, and which has an electrician or someone who said this machine is pukka. And then I apply that test; a very quick non-invasive test. I can do a heart trace in here [the GPs office] to see if I can spot anything as well GP1

Conversely, S2 suggested that home-monitoring may be more accurate than office-based monitoring due to white-coat hypertension, and the fact that home-based monitoring may happen over a longer period of time. Understanding the patients motivations The patients motivations for recording the data was also a factor in determining whether the data should be used. Pertaining the caffeine chart, GP3 stated a need to understand why the patient recorded it, when it is not a normal thing to do: I would try and ask a little bit more about this [referring to caffeine chart] and why she's done this anyway, just to have an understanding, you know, of reasons, because not everyone charts their caffeine intake. GP3

In particular, S3 suggested that the presentation of the caffeine chart was a way of indirectly telling him that there are underlying psychological issues, such as being overwhelmed and struggling with their studies or job. Referring to both scenarios, S5 asserted that the patient was obsessive to record both the data, suggesting an underlying psychological issue. The mere existence of the heart rate plot provoked a similar jump to psychological issues with S4: Theyre faking it. If

| | Self-recorded data | | | | | | | | | | | | | | Other forms of data | | | | | | | |
Factor	[9]	[4]	[7]	[30]	[2]	[26]	[31]	[25]	[5]	[3]	[17]	[39]	[8]	[27]	[29]	[36]	[21]	[12]	[34]	[18]	[24]	[13]
Data capture																						
irrelevant/useless	■	■				■											■		■			
poor data quality				■		■			■	■	■			■					■			■
data incomplete		■	■			■			■			■	■						■		■	
Data access																						
data representation	■	■	■								■											
selective disclosure	■	■						■					■									
poor interoperability	■	■	■					■			■				■			■		■		
Clinical practice																						
interpretation													■	■								
no data analysis training	■		■		■		■												■		■	■
takes time away from patient	■								■						■	■		■	■			
professional autonomy								■													■	
legal issues			■	■				■														
Situational constraints																						
time pressure	■															■	■		■		■	
information overload			■	■													■					
not worth clinician effort	■																					

Table 1. Major themes

Factor	Explanation	Implications for use of patient-provided data	Literature sources
Contextualisation	*Priming* - exposure to one piece of information influences how another piece of information is perceived. • *Availability* - the disposition to judge things as being more likely or frequently occurring if they readily come to mind, such as recent information. • *Framing* - the way in which a problem is presented affects the outcome of a task. • *Risk taking* - clinicians switch between risk aversion and risk taking depending on whether the problem is expressed in terms of the possibility the patient might die or live.	Clinicians see many patients, and their prior decisions or interpretations made with patient-logged data may change how they use new data. Therefore, some pieces of information may become disproportionately relied upon based on inaccurate estimates of frequencies. Further, the patient's approach to providing their data (e.g., why they recorded it) may contribute to a clinicians framing of the problem. This has strong implications for how data may be presented by a patient, and the order data are presented in.	[28], [22], [10],
Information interpretation	• *Illusory patterns* - seemingly meaningful relationships are seen in random data which, despite their statistical insignificant, may be used to influence a decision. • *Representativeness* - when presented with information specific to a patient, other sources of data are neglected (e.g., base rates of a particular disease). • *Anchoring and adjustment* - the tendency to perceptually lock onto prominent features in a patients presentation too early in the diagnostic process, and failing to adjust this initial impression in the light of later information. Anchoring has been found to lead to premature decision making with patients being labelled with a diagnosis early in presentation. • *Base rate neglect* - statistical significance of an observation has little influence on its importance in reasoning.	Errors made during information processing may may lead to misdiagnoses, rationalising unusual diseases, overutilisation of resources, and contribute to inaccurate estimates of base rates. An observer's ability to appraise the importance of particular pieces information over others may lead a physician to ignore critical pieces of data that were not among those first noticed, such as base rate, the patient's presentation or the patient's medical record.	[38], [22], [**?**], [6], [10], [**?**]
Metacognition	• *Affect heuristic* - a clinician's emotional state can significantly affect their interpretation of patient data and their decisions • *Confirmation bias* - findings are emphasised based on if they support one's own desires or beliefs • *Selective exposure* - people are less willing to eliminate an original hypothesis, with a person attributing unjustified rationality to that hypothesis based on their pre-existing views. • *Ambiguity effect and outcome bias* - if the probability of favourable outcome is only available for some options, other options tend not be considered, also causing the belief that favourable outcomes are more likely. • *Functional fixedness* - limitations of tools or analysis techniques may lead to a relying on known examples, which may limit insights which may be gained from data • *Appropriation difficulty* - problem solving has been demonstrably less effective when a solution requires atypical use of an object	Data interpretations and decisions made using data are ways impacted by emotion and irrational belief in an original hypothesis, despite evidence to the contrary. This may lead to errors and adverse events including incorrect and missed diagnoses. Further, the inability of a clinician to use appropriate data effectively increases the time cost of using data, and limits the capability of a clinician to gain insight from data. In specialist clinical roles, this may lead to only using data in ways that they have been trained in their specialism.	[22], [16], [**?**], [37], [10], [15], [1], [19]

Table 2. Implications from bias when there are time constraints, constraints on how data may be controlled, or it is not clear how data should be used

someone brought this chart to me, theres a red flag that this guys got psych issues S4

Although S3 raised that its common for engineers to bring in these kinds of plots, and S7 proposed that patients bringing in data will become normal practice, the need to understand why the patient recorded the data remained a common theme throughout the discussions. S6 said that a lot of patients come with a diagnosis that they put on, with S1 following on from this by saying: It's typical that patients like this that come in and they give you, you get this whole story, and then they want you to focus on this it and it takes your attention away, or they're going to tell you this is the reason why all of this is going on, and then you have to say well ok but let's just put that there. S1

GP3 also needed to understand why both patients had brought the charts, expressing confusion at their presentation. He wanted to understand what these patients wanted out of their consultations. if all that are normal, and she's still feeling, you know, then again, I would then refer back to that [the chart], especially if she's quite... a student and knowledgeable about that, might be cause to listen. "Hang on, OK, tell me more about this, and why? You know, why are you doing that?". GP3

GP1 explained that there is a lot of pressure for GPs to prescribe, and that it was necessary to resist this, because patients push for prescriptions of poorly evidence based things. Deciding how to use the patient-provided data In deciding how the patient-provided data should be used or not, S1 explained that they needed to initially make a decision on how long to spend looking at it I mean I think when you look at something like this you do have to be able in your own mind to say, OK am I going to spend 30 seconds on this, or am I really going to spend more time and give it more importance?Aand I think that's what we face a lot. S1

S1 explained that these information sources will add layers of data assessment to his practice, and questioned whether this patient-provided information may adversely affect efficient work flow The layers of information, data assessment You know, it's ramping up and and all of these devices are certainly adding or could and will add yet more of this, you know, data that, you know, you know Certainly here we get a lot of things faxed to us. We get to know patients who come here and then they go somewhere else. But then we are getting their lab work over and over againtheir X-rays, their visits. And you know at some point you have to ask yourself, you know, what is efficient here and what is not? S1

S7 concurred, explaining that this adds complexity to an already complex medical interface. When asked if patient-provided information is a good or a bad thing, there was general agreement within the room. S4 suggested that age of the clinician may be a large factor in acceptance of patient provided data arguing that medics are creatures of habit, who do not usually change their practice significantly if their current work practice satisfies their demands (???) Newly-trained young doctors may become used to patients bringing their own data. He foresaw not changing his own practice

within the next 10 years. Whereas the younger doctors that are coming in are seeing patients for the first time and they're used to people bringing in this kind of stuff and will put more thought into it rather than... Doctors are typically creatures of habit. You've been doing something for ten, fifteen years the same way, you're going to carry on doing it. There are minor changes that happen in terms of pathology and diagnostics, but in general you're used to doing it in a certain way... So I think it remains to be seen, but, you know, when I think what I'll be doing in 10 years time in terms of how I'll be managing a patient, it will be very similar. S4

Need for physical exam, scenario and data alone was not enough. e.g. for ruling out neurological causes.

> "I haven't even touched him yet. and then I'd do after my history, then I'd do an examination, again feeling the pulse myself, feeling is it strained, quality, character, whether I can do anything to the pulse, and then listening to his heart and doing the various movements and motions sit forward sit back, to see if he's got any murmurs associated with this. see if he's been compliant with his anticoagulants, maybe he is maybe he isn't." GP1

Using (or ignoring) the patient-provided data There were stark differences in how useful the clinicians found the patient-provided information. GP3 chose to ignore the caffeine, he stated that it was irrelevant, but conceded that he may be wrong and may come back to it later. Despite stating that he would also ignore the heart rate plot and it would not have much influence on his decisions, he did observe that there were high peaks, which motivated questions about what the patient was doing at those times. But certainly, you know, I don't think this [chart] would influence, but I would, you know, the only influence it would have is to try and understand more about why he did this and what he wants out of the consultation GP3

S4 said the heart rate was underwhelming, essentially showing normal heart rate other than twice. GP2 said that the information conveyed in the heart rate plot was not significant, with high rates explained by any activity he could have been doing at the time. GP2 said that blood pressure would have been more useful to her.

S4 stated that the presentation of this information would sway him toward caffeine as a cause: I think if you see her at the office and she brings you this immediately you start thinking you know, this is all from too much caffeine. S4

GP1 said the caffeine chart suggested a coffee-withdrawal headache. He verbalised a unit conversion in trying to understand how much caffeine 400mg is. right! this could be a coffee headache. Well if you stop drinking coffee you get a headache, if you start drinking coffee you get a headache. Daily consumption – WOW! - above 400mg - 150mg per cup. Yeah, so this could be a coffee withdrawal headache. GP1

GP1 went on to suggest that he might advise the patient to have a graded reduction in caffeine. Note in the quote above that GP1 was able to make a unit conversion of caffeine to cups of coffee, and was also able to note that this is an ex-

cessive amount. S2, S3 and S5 said they did not know what a normal caffeine level is. Similarly, although S2 made an initial observation of the heart rate chart based on his own beliefs of how heart rate varies, he said he would need to consult a cardiologist to fully understand it: Well one thing that struck me is how little variability there was in the heart rate during the time of the day. I thought that was, I would need to ask a cardiologist, but I thought there was greater variability in heart rate. S2

Pattern recognition, realising it might not be anything because I dont know what it is, the other things is - its funny on the charts - the last three days are kinda an uptrend. so maybe go talk to the patient and ask: why now, for the last three or four days, are they slowly going up? Whereas before it was up and down. It might not be anything. S6

One hospital specialist said he would elicit this information directly from the patient. This need for the patient in the room was reciprocated by one GP, who explained that they observe how the patient behaves - how they walk in the room, how they sit down. the way they sat, or something else, or stomping gate, or something. you're eyes just think oh! and then your connection will be made consciously and unconsciously GP1 Using patient-provided data to support risk averse workflow S1 made connections between the cases, GP2 used prior experience

Both S3 and S4 explained that they reflect on the scenarios based on their own experience and training within their specialisms as a pulmonologist, which I am, you know, I noted the history of asthma, and I said whatever's going on is not exacerbating her asthma S3

Linking, unifying we as physicians - how we're trained - I can't help but try to figure out a way to lump all this together, to come with one unifying diagnosis. S2 what are the details of the timeline really, the timeline. Is this a distinct event or are this linked somehow, and pull it out from her, the history. S2

S5 also looked for the worst possible thing really just looking for things that are more serious, like trying to see what's the worst possible thing that she could have, approaching it that way. And hopefully it will turn out to be nothing. but I guess thats, usually, I'm always looking for what's the worst possible thing the person could have and work backwards from there. S5

GP1 checks with other GPs. GP1 - common things are common, common presentations of rare conditions are less common than rare presentations of common conditions.. GP1 said that the knowledge of caffeine consumption changed his perspective on possible causes, though said that although caffeine may seem likely, there could be a far more serious tumor. On the other hand, you have to be economic. A plan which is both economic and risk averse but at the moment I've chopped chopped chopped chop, and we come to here. And now I think right, we've pruned off all of that, now I've got the bare tree - it's distiguous, not perennial. and it's very easy to see, this is my path now. it's your heart, mate. and I need to do just one or two tests to show otherwise this tree...

this root or trunk, becomes thicker and I will go that way. that's how I think. GP1

Summary of findings

DISCUSSION

Implications for design

Limitations

Future Work

it's not just what the data is, it's who it comes from your friend, your colleague, your doctor. is it a teenager, a female student, a male student, a middle aged man, a middle aged woman

CONCLUSIONS

REFERENCES

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