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Web Science CDT

# The Dangers of Patient Data in Clinical Decision Making

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September 3, 2014

A dissertation submitted in partial fulfilment of the degree of

MSc Web Science

## Abstract

The increasing ubiquity of personal tracking devices is leading to the possibility of using this data to support clinical decisions. Thousands of devices exist to record personal information related to health, including weight, diet and activity. Such data has been demonstrated as providing self-insight and promoting positive health behaviours, such as maintaining a healthy diet. As such, there has been interest in its use by healthcare practitioners to support decision making. However, such data may have insufficient context, leading to biased decisions and poor judgement.

Through surveying the use of personal data within constraints, such as time and context, this dissertation synthesises a series of cognitive biases pertinent to a number of healthcare scenarios. From this, the dangers of their use in healthcare are assessed against their potential benefits. In agreement with previous research, the biases pose a greater risk within thin-slice scenarios then those with resource-rich. [Results will be discussed here] Drawing from these results, this dissertation forms the design of a study which will examine the prevalence of such biases within nursing when providing care to stroke patients.

# Contents

# 6 Methodology

This section describes the methodology used to form an understanding of biases which affect evidence-based clinical decision making. Twelve relevant biases are identified, then an overview of a literature synthesis procedure follows.

## 6.1 Identifying Relevant Biases

The underlying biases which affect all clinical decision making are first identified. Following this, the biases which affect data interpretation are identified. These are combined to form a list of 12 Clinical Interpretation Reasoning Biases.

### 6.1.1 Cognitive Dispositions to Respond

As discussed in Section 4, there is little research into the effects of biases in clinical decision-making. Croskerry (2002) lists 30 biases and heuristics which affect clinical decision making, collectively called Cognitive Dispositions to Respond (CDRs). These are listed in 1. For each, Croskerry describes its effect on clinical decision making, both in terms of what may be observed and the potential consequences, and provides a discussion on how they may be avoided, citing existing empirical studies.

The CDRs identified by Croskerry (2002) affect all clinical decisions, and are thus of key importance in identifying biases which affect evidence-based clinical decision making. Thus, when a clinician must make a decision based on a patients presenting complaints, their decision is also affected by CDRs (see Figure 1).

### 6.1.2 Interpretation Biases

Section 3.3 identified a number of biases which affect the interpretation on data. In particular, the 10 listed in Table 2 will be described as the Interpretation Biases (IBs). These biases are importance to evidence-based clinical decision making as they affect how evidence is identified within patient data (see Figure 2).

Table 1: 30 Cognitive Dispositions to Respond identified by Croskerry (2002). Those in bold are pertinent to external stimuli.

| | | |
|---|---|---|
| Aggregate bias | Gender bias | Psych-out error |
| Anchoring | Hindsight bias | Representativeness restraint |
| Ascertainment bias | Multiple alternatives bias | Search satisfying |
| Availability and non-availability | Omission bias | Sutton's slip |
| Base-rate neglect | Order effects | Triage-cueing |
| Commission bias | Outcome bias | Unpacking principle |
| Confirmation bias | Overconfidence bias | Vertical line failure |
| Diagnosis momentum | Playing the odds | Visceral bias |
| Fundamental attribution error | Posterior probability error | Yin–yang out |
| Gambler's fallacy | Premature closure | Zebra retreat |

Table 2: Interpretation biases

| | | |
|---|---|---|
| Affect heuristic | Curse of knowledge | effect |
| Ambiguity effect | Framing effect | Probability neglect |
| Illusory patterns | Functional fixedness | |
| Priming | Observer expectancy | Extension neglect |

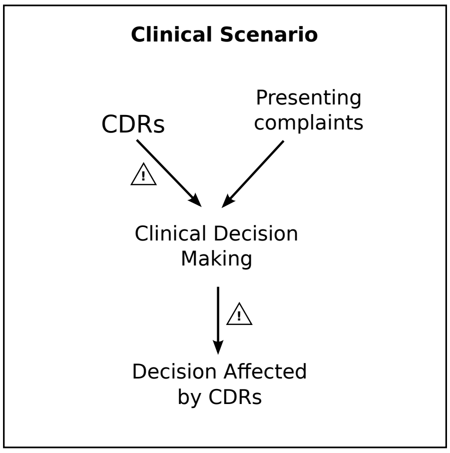


Figure 1: Biases in clinical decisions

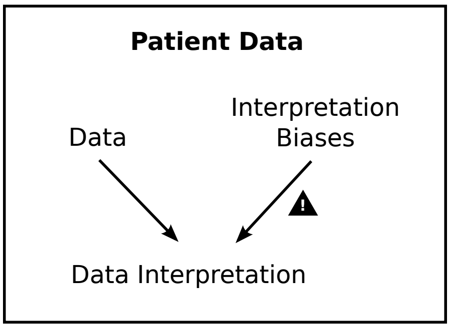


Figure 2: Biases in patient data interpretation

### 6.1.3 Clinical Interpretation Reasoning Biases

Having identified the biases which affect clinical decisions (CDRs) and the biases which affect data interpretation (interpretation biases), the biases which affect evidence-based decision making can be deduced.

In an evidence-based clinical decision, the clinician must interpret patient data prior to making a clinical decision, therefore interpretation biases affects cognitive dispositions to respond. This is shown in Figure 6.2. Thus, it can be said that the CIRBs are the union of interpretive biases and cognitive dispositions to respond affected by interpretive biases. This can be expressed in the following formula:

$$CIRB = IB + IB(CDR)$$

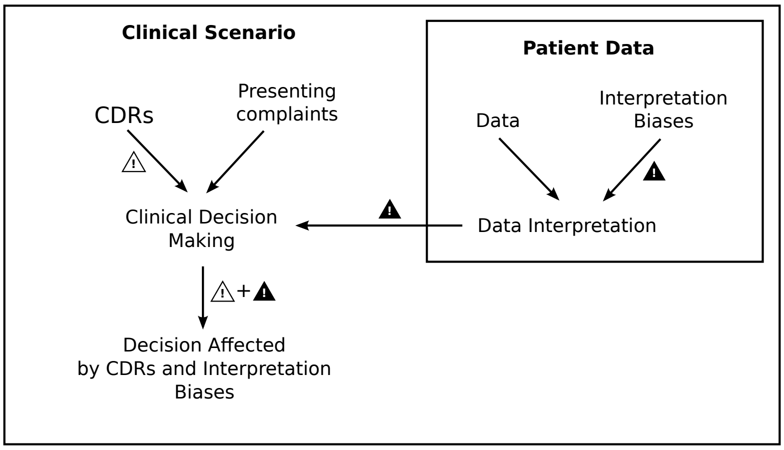


Figure 3: Biases in evidence-based clinical decisions

Table 3: 11 Cognitive Dispositions to Respond affected by interpretation biases ($IB(CDR)$).

| | | |
|---|---|---|
| Aggregate bias | Base-rate neglect | Outcome bias |
| Anchoring | Confirmation bias | Posterior probability error |
| Ascertainment bias | Fundamental attribution error | Representativeness restraint |
| Availability and non-availability | Order effects | |

Where IB is the set of Interpretive Biases and CDR is the set of Cognitive Dispositions to Respond.

Eleven CDRs are affected by IBs, which are listed in Table 3. For the purpose of this dissertation, only those which have changed will be discussed. Croskerry (2002) may be reviewed for details on those which are not modified.

Using this approach, 12 CIRBs were identified, listed in Table 4 Those biases which are similar have been grouped together.

## 6.2 Literature Synthesis

Due to the multidisplinary nature of technology and healthcare, a Web Science approach has been applied to understanding bias within this space. As such, this dissertation will

Table 4: Clinical Interpretation Reasoning Biases.

| | | |
|---|---|---|
| Affect heuristic | Confirmation bias | Framing effect |
| Ambiguity effect *and* Outcome bias | Priming, Order effects, contrast effect *and* posterior probability | Functional fixedness |
| Anchoring and Adjustment | Curse of knowledge | Observer-expectancy effect |
| Availability heuristic | Extension neglect *and* base rate neglect | Probability neglect |
| Illusory patterns *and* Aggregate bias | | Ascertainment *and* Observer-Expectancy |

take the form of a literature review, considering material from both health sciences, computer science and cognitive sciences to build a picture of the dangers of bias in personal informatics within healthcare. From this, 16 biases have been identified, and their risks considered in two forms of healthcare scenarios – those with large context, and those will little context. This dissertation proposes that biases more prevalent within little context scenarios pose a large risk to decision-making, and that risks may be reduced through the design of personal informatics and careful consideration into how personal informatics may be implemented within Healthcare.

Literary synthesis Identification of biases Classification by context Identification of existing relationships between taxonomy and data

For each bias: description description [+ empirical] inclusion justification - why does it affect interpretative decisions? clinical consequences, example scenarios + relevant literature (largely grounded in the works of Croskerry2002) High and Thin-slice risk summary empirical evidence of relation between context (uncertainty, knowledge, time, resources) and bias conclusion

In terms of patient data, biases affect how data is interpreted (which I will call Interpretation Biases). Those biases thus get carried through to clinical decision making. Decisions are therefore affected by both CDRs and Interpretation Biases, as shown in Figure .

## 6.3 Identifying Scenarios

Scenarios:

**Thin-slice** : A+E, quick decisions, automatic

**Resource-rich** : General Practice, slow decisions, reflective

# 7 Results

This section gives an overview of the results from the literature synthesis.

## 7.1 Biases which affect evidence-based clinical decision making

Table 5 lists 11 Clinical Interpretation Reasoning Biases, with a description and consequences, risk to thin-slice scenarios and risk to resource-rich scenarios.

## 7.2 Effects of bias in thin-slice scenarios

A thin-slice scenario is a clinical scenario in which there is heavy time constraints, little access to information and no clinical patient history. It is expected that judgements in thin-slice scenarios are more susceptible to biases. Accordingly, table 5 show that 10 out of the 11 CIRBs are prevalent in thin-slice scenarios. Among these, it appears that the reasons are fourfold: false pattern recognition, positive tendency, misuse of prior knowledge and poor communication.

**False pattern recognition.** The biases which are caused by pattern recognition under uncertainty include representativeness heuristic, extension neglect, base rate neglect, illusory patterns and aggregate bias. It has been proposed that, when interpreting data or making decisions under uncertainty, clinicians are more likely to observe pattens which are statistically insignificant (Kahneman and Tversky, 1974b), and use these without consideration of the statistical significance (Kahneman and Tversky, 2000). As has been found by (Bassili and Krosnick, 2000), time constraints leads to identification of false patterns. Kahneman and Tversky (1974a) and Bar-Hillel (1980) propose that information considered important will outweigh base-rates. Therefore, in uncertainty, clinicians are likely to make decisions based on false-patterns over base rates.

**Positive tendency.** The biases which are caused by positive tendency under uncertainty include the affect heuristic, the ambiguity effect, outcome bias the framing effect. In thin-slice scenarios, there is a greater dependency on emotion in making decisions, with people more prepared to choose an option if it has favourable outcomes as more competent (Baron and Hershey, 1988). People will choose favourable options based on their probabilities despite not knowing the probabilities of other options (Ellsberg, 1961). Further, people are more likely to choose options when they are phrased positively (Kahneman and Tversky, 1981).

**Misuse of prior knowledge.** The biases which are caused by misuse of prior knowledge include priming, order bias, contrast effect, posterior probability error, anchoring, the availability heuristic, confirmation bias, observer-expectancy effect and the ascertainment bias. These biases affect judgements using: knowledge about previous judgements (Meyer and Schvaneveldt, 1971; Kahneman and Tversky, 1974b); perceived weightings of knowledge (Kahneman and Tversky, 1973); or personal beliefs (Mahoney, 1977). In cases of constrained time or resources, the biases cause people to use prior knowledge without consideration of its reliability or relevance.

**Poor communication.** Only one identified bias relates to poor communication: the curse of knowledge. This causes those who are more knowledgeable in a particular area to communicate in a way that may not be understood by a less informed person (Colin Camerer et al., 1989). This acts two ways: from the clinician to the patient, and from the patient to the clinician. In thin-slice scenarios, there is little available knowledge about patients meaning clinicians are more likely to communicate ineffectively (Kennedy, 1995).

## 7.3 Effects of bias in resource-rich scenarios

A resource-rich scenario is clinical scenario in which there is sufficient time, access to supplementary information and clinician-patient history. It is expected that judgements in resource-rich scenarios will be less susceptible to biases. Accordingly, table 5 show that 3 out of the 11 CIRBs are prevalent in resource-rich scenarios. The causes of these are related to the specialisation of the clinician.

**Specialisation.** The biases which are caused by the specialisation of the clinician include confirmation bias (observer-expectancy effect, ascertainment bias), functional fixedness and representativeness heuristic (extension neglect and base rate neglect). The frequent use of tools leads to not considering atypical uses of the tools (Adamson, 1952). The prior experiences of clinicians will lead them to weight their beliefs heavily, influencing their judgements Wason (1960). These experiences and beliefs cause neglect of base-rates and an over-willingness to accept one's own beliefs.

Table 5: Clinical Interpretation Reasoning Biases with descriptions and consequences, risks to thin-slice scenarios and risks to resource-rich scenarios.

| Cognitive Bias | Description and Consequences | Risk to thin-slice scenarios | Risk to resource-rich scenarios |
|---|---|---|---|
| Affect heuristic | Decisions are influenced by current emotions, such as happiness or sadness (Zajonc, 1980). Zajonc (1980) states that affective reactions are often the first reactions of humans and made more quickly and confidently than cognitive judgements. Thus, a clinician's emotional state can significantly affect their interpretation of patient data and their decisions. Findings by Croskerry et al. (2010) support this, with the emotional state of a clinician potentially leading to biased decision making, errors and adverse events. | High. Kahneman and Tversky (1974a) state that decisions under uncertainty lead to a greater dependence on heuristics and intuition. Croskerry et al. (2010) found that when intuition is relied upon, clinical reasoning is particularly susceptible to the affect heuristic. It has also been found that people heavily rely on affect in time-pressured and high risk situations (Finucane et al., 1998). In one study, being sad leads to a greater affect in thin-slice scenarios (Ambady and Gray, 2002). Therefore, the affect heuristic is of high risk in thin-slice scenarios. | Low. Finucane et al. (1998) found that, given sufficient time and resources, the affect heuristic will be less relied upon. Therefore, the affect heuristic is of low risk in resource-rich scenarios. |
| Ambiguity effect and outcome bias | If the probability of having a favourable outcome is only available for some options, other options tend not be considered, and by extension, causes the belief that favourable outcomes are thus more likely (Ellsberg, 1961). Clinicians must often make decisions with only limited information about outcomes (Cioffi, 1997). The information retrieved from patient data may greatly influence the availability of such information. Croskerry (2002) has proposed that such biases reduce clinicians' objectivity, compromising the process of reasoning, potentially leading to errors and adverse events. | High. More limited resources leads to greater uncertainty. When making decisions in uncertainty and descriptions of outcomes are available, Baron and Hershey (1988) found that people rated the favourable outcome as a better, more competent decision. Therefore, the ambiguity effect and outcome bias are of high risk in thin-slice scenarios. | Low. With greater resources (time and information), uncertainty is reduced (Kahneman and Tversky, 1974a), allowing for more objective reasoning (Mellor, 1983). Therefore, the ambiguity effect and outcome bias are of low risk in resource-rich scenarios. |

Table 5: Clinical Interpretation Reasoning Biases with descriptions and consequences, risks to thin-slice scenarios and risks to resource-rich scenarios.

| Cognitive Bias | Description and Consequences | Risk to thin-slice scenarios | Risk to resource-rich scenarios |
|---|---|---|---|
| Anchoring and adjustment | A greater importance is placed on the first piece of information offered when making decisions (Kahneman and Tversky, 1974b). Anchoring can affect data interpretation by biasing an observer's ability to place values to particular pieces of information (Kahneman and Tversky, 1974b). This may intern affect the decisions they make based on the data. Anchoring has been found to lead to premature decision making with patients being labelled with a diagnosis early in presentation (Croskerry, 2002). | High. In thin-slice scenarios, there is little available knowledge about patients. Mussweiler and Strack (2000) demonstrate that with less knowledge about a target, there is a greater reliance on an anchor when reasoning about it. Furthermore, (Mussweiler and Strack, 2000) show that even when participants have control over their anchor values, the effects still hold. Therefore, anchoring is of high risk in thin-slice scenarios. | Low. With greater knowledge available about a target, it has been shown that there is less reliance on an anchor (Mussweiler and Strack, 2000). Therefore, anchoring is of low risk in resource-rich scenarios. |
| Availability heuristic | Information which is considered more important, such as recent information, is judged more frequent and therefore more heavily relied upon for decision making (Kahneman and Tversky, 1973). When interpreting data, the availability heuristic can cause some pieces of information to become disproportionately relied upon than others based on incorrect estimates of frequencies. For example, it has been found that it is easier to recall frequent observations than infrequent ones (Clore and Gerrod, 1991). Croskerry (2002) finds that the availability heuristic can lead to disproportionate perceptions of frequencies, leading to tendencies to make diagnoses based on information which appears more important. This can thus lead to incorrect diagnoses. | High. Kahneman and Tversky (1974a) state that decisions under uncertainty lead to a greater dependence on heuristics. Having limited time and resources leads to focus on the little available information (Croskerry, 2002), thus leading to a more subjective decision. This has been shown to lead to a greater dependence on the availability heuristic in decision-making (Wänke et al., 1995). Therefore, the availability heuristic is of high risk in thin-slice scenarios. | Low. Having access to relevant resources leads to more objective judgements (Mellor, 1983), leading to a lesser reliance on the availability heuristic (Wänke et al., 1995) Therefore, the availability heuristic is of low risk in resource-rich scenarios. |

Table 5: Clinical Interpretation Reasoning Biases with descriptions and consequences, risks to thin-slice scenarios and risks to resource-rich scenarios.

| Cognitive Bias | Description and Consequences | Risk to thin-slice scenarios | Risk to resource-rich scenarios |
|---|---|---|---|
| Confirmation bias, observer-expectancy effect and Ascertainment bias | One's own beliefs influence judgements and decisions (Mahoney, 1977). The tendency to emphasise information which supports one's own beliefs, and refute information which does not, has been widely discussed (Mahoney, 1977). There is thus risk that clinicians may tend to interpret patient data in ways that only support their own views or hypotheses. Croskerry (2002) argues that clinicians make diagnoses base on what they hope to find. The estimates of frequencies of diagnoses affect how judgements are made on patient data and subsequent decisions due to the availability heuristic (Kahneman and Tversky, 1973). This may lead to the preservation of weak hypotheses and diagnoses, despite evidence to the contrary, leading to missing a correct diagnoses (Croskerry, 2002). These biases can thus lead to inaccurate estimates of the frequencies of diagnoses (Croskerry, 2002). For example, if a patient has been non-compliant in taking medication for heart failure, the clinician is more likely to find evidence of congestive heart failure (Croskerry, 2002). | High. Time constraints limit the processing of new information, leading to a less informed conclusion thus less information to refute an original hypothesis or a clinician's personal beliefs (Nisbett and Ross, 1980). Further, within situations in which variables are unknown, it has been found that people are less willing to eliminate an original hypothesis, with that person attributing unjustified rationality to that hypothesis (Wason, 1960). Therefore, confirmation bias is of high risk in thin-slice scenarios. | Medium. Trained clinicians will be more familiar with data sources, such that tendencies to rely in heuristics and readily available information are reduced (Croskerry, 2002). When time and resources are less constrained, clinicians are more likely to make greater use of evidence to refute weak hypotheses (Wason, 1960). However, Wason (1960) has shown confirmation bias to persevere despite more the potential for more informed conclusions, perhaps due to perceived high experience. Therefore, confirmation bias is of medium risk in resource-rich scenarios. |

Table 5: Clinical Interpretation Reasoning Biases with descriptions and consequences, risks to thin-slice scenarios and risks to resource-rich scenarios.

| Cognitive Bias | Description and Consequences | Risk to thin-slice scenarios | Risk to resource-rich scenarios |
|---|---|---|---|
| Curse of knowledge | People who are more informed on a particular subject are unlikely to think about it from the perspective of less informed people (Colin Camerer et al., 1989). It affects communication between clinician and patient, which is important for informing how patient data is interpreted. It thus acts two ways: the ability for a clinician to inform patient, and the ability for a patient to inform the clinician. The knowledge overlap between clinician and patient is typically small, leading to incorrect perceptions about each other's level of understanding (Birch and Bloom, 2007). Clinicians must therefore have an understanding of the knowledge overlap in order to avoid the curse of knowledge. If clinicians lack understanding about a patient, and subsequently patient data, they are more likely to make decisions based in illusory patterns (Whitson and Galinsky, 2008) and heuristics (Kahneman and Tversky, 1974a), in turn potentially leading to incorrect diagnoses (Croskerry, 2002). | High. In thin-slice scenarios, there is little available knowledge about patients and prior contact with the patient cannot be assumed. This means clinicians are not aware of the knowledge overlap and are more likely to communicate ineffectively (Kennedy, 1995). Therefore, the curse of knowledge is of high risk in thin-slice scenarios. | Low. Frequent contact between clinician and patient and less constraints on time allows for increased communication, thus making available more information about them. Increasing the amount of available information about a person has been demonstrated to reduce the curse of knowledge (Kennedy, 1995). This has also been demonstrated in a paediatric clinic, where mothers who frequently met with clinicians demonstrated more effective communication (Korsch and Negrete, 1972). Korsch and Negrete (1972) further showed that increased contact time lead to more personal and friendly communication, leading to more effective communication. Therefore, the curse of knowledge is of low risk in resource-rich scenarios. |
| Framing effect | The way a problem is stated affects the outcomes (Kahneman and Tversky, 1981). Framing affects how people make a decision based on whether it is phrased positively or negatively. It pertains to both how pieces of information are interpreted and how subsequent clinical decisions are made. (Kahneman and Tversky, 1981) state that clinicians have been observed in switching between risk aversion and risk taking depending on how a problem is presented. Thus, clinicians are at risk of basing risk on how a problem is presented over other evidence which is available, leading to poor judgement in interpretation and decision making. | High. Time limitations have been shown to lead to a greater effect from framing (Takemura, 1992). Takemura (1992) demonstrated that when options were phrased positively according to their gains, the least-risk option was chosen. Conversely, when the options were phrase negatively according to their losses, the highest-risk option was chosen. Therefore, the framing effect is of high risk in thin-slice scenarios. | Low. Takemura (1992) demonstrated that when subjects where given sufficient time to think about problems in more depth, the framing effect was not observed. Therefore, the framing effect is of low risk in resource-rich scenarios. |

Table 5: Clinical Interpretation Reasoning Biases with descriptions and consequences, risks to thin-slice scenarios and risks to resource-rich scenarios.

| Cognitive Bias | Description and Consequences | Risk to thin-slice scenarios | Risk to resource-rich scenarios |
|---|---|---|---|
| Functional fixedness | People are limited to using an object only in the way it was intended (Adamson, 1952). Clinicians may be limited to using a data source for some 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 (German and Barrett, 2005). This limits the capability of a clinician to gain insight from patient data, leading to less informed decisions and risk-averse diagnoses. | Low. It can be expected that clinicians in thin-slice scenarios use the same data source infrequently, and may regularly use data sources which are unfamiliar to them. Adamson and Taylor (1954) demonstrated that functional fixedness decreases when the amount of time between uses of an object increases and showed that functional fixedness results from pre-utilisation of objects. Therefore, functional fixedness is of low risk in thin-slice scenarios. | High. According to the research by (Adamson and Taylor, 1954), given the expectation that clinicians may use similar data sources frequently, functional fixedness may affect resource-rich situations more. Therefore, functional fixedness is of high risk in resource-rich scenarios. |
| Illusory patterns and aggregate bias | Given a distribution, clusters of data points or associations between data points may be observed and, despite their statistical insignificance, be used to influence a decision (Kahneman and Tversky, 1974b). These biases affect data interpretation, and thus can ultimately affect clinical decision making (Whitson and Galinsky, 2008). It may thus be used by clinicians in rationalising an atypical diagnosis for a patient with a particular condition based on such bias (Croskerry, 2002). In one psychological test, patients are given an inkblot and asked to identify details. Chapman and Chapman (1969) showed that clinicians were likely to associate patients who identified buttocks or genitalia with homosexuality, despite research showing heterosexuals were just as likely to make such observations. This was more probably associated with clinicians' expectations of stereotypes (Kahneman et al., 1982). | High. Time-constrained and information-limited decisions have been shown to lead a greater chance of false patterns being recognised (Bassili and Krosnick, 2000). Loss of control over data has been shown to lead to greater illusory pattern perception (Whitson and Galinsky, 2008). Insufficient understanding of relevant research, or lack of familiarity with an individual patient, leads to reliance on stereotypes Chapman and Chapman (1969). Therefore, illusory patterns and aggregate bias are of high risk in thin-slice scenarios. | Low. With less time and resource constraints, and greater control over the data, illusory patterns have been shown to become less frequent (Bassili and Krosnick, 2000; Whitson and Galinsky, 2008) Therefore, illusory patterns and aggregate bias are of low risk in resource-rich scenarios. |

Table 5: Clinical Interpretation Reasoning Biases with descriptions and consequences, risks to thin-slice scenarios and risks to resource-rich scenarios.

| Cognitive Bias | Description and Consequences | Risk to thin-slice scenarios | Risk to resource-rich scenarios |
|---|---|---|---|
| Priming, order bias, contrast effect and posterior probability error | Exposure to one piece of information influences how another piece of information is perceived (Meyer and Schvaneveldt, 1971). There are two prime cases where this is concern: priming between patients, and priming between patient data sets (Croskerry, 2002). 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. Priming is therefore an important consideration in both patient data interpretation and subsequent decision making. Furthermore, it has been found that the performance of an individual changes as they are exposed to repeated similar tasks (Wundt, 1980). Earlier decisions or interpretations therefore affect the performance of later decisions or interpretations. A clinician may base their diagnoses on their perceived likelihood of a particular disease, which may be influenced by what the clinician has observed previously, which may result in an incorrect diagnoses (Croskerry, 2002). | High. Tourangeau and Rasinski (1988) state that a decision is made based on beliefs which are primed by prior items, and these beliefs are more prone to carry over when frequent familiar decisions are made. It has been established that priming occurs frequently in triage nurses because they must make frequent familiar decisions (Reay and Rankin, 2013). Reay and Rankin (2013) further link time pressure and high stakes of a thin-slice context to lead to greater occurrence of priming. Therefore, priming is of high risk in thin-slice scenarios. | Low. Less frequent and more diverse problems lower the risk of priming Tourangeau and Rasinski (1988). Availability of time and informational resources leading to more informed beliefs and more objective decisions (Mellor, 1983), thus reducing the risk of priming Reay and Rankin (2013). In the model of priming proposed by Tourangeau and Rasinski (1988), well informed beliefs are more relied upon than primed beliefs. Therefore, priming is of low risk in resource-rich scenarios. |

Table 5: Clinical Interpretation Reasoning Biases with descriptions and consequences, risks to thin-slice scenarios and risks to resource-rich scenarios.

| Cognitive Bias | Description and Consequences | Risk to thin-slice scenarios | Risk to resource-rich scenarios |
|---|---|---|---|
| Representativeness heuristic, extension neglect and base rate neglect | The statistical significance of an observation has little influence on its value in reasoning (Kahneman and Tversky, 2000). When clinicians use patient data, their observations ultimately affect decision making. Extension and base rate neglect affect how this data is interpreted in terms of placing value to observations. If statistical significance of observations is not used in valuation, overestimates of unlikely diagnoses may occur (Croskerry, 2002). | High. Kahneman and Tversky (1974a) state that decisions under uncertainty lead to a greater dependence on heuristics. The degree of use of base case is dependent on knowledge of it, which may not be available in thin-slice scenarios due to limited time and informational resources (Kahneman and Tversky, 2000). Bar-Hillel (1980) argues that people order information in degree of relevance, such that when relevant information about a subject is provided, the base rate is weighted lower and subsequently ignored. However, in thin-slice scenarios, interpretive biases and uncertainty may lead to erroneous observations about data (Kahneman and Tversky, 2000). Base rates may subsequently be ignored in favour of poorly judged information. Therefore, extension neglect and base rate neglect are of high risk in thin-slice scenarios. | High. More time leads to greater potential to understand the quantifiable data (Kahneman and Tversky, 2000). Less time constraints leads to greater potential to understand the quantifiable data (Kahneman and Tversky, 2000). Greater knowledge about particular information leads to more rational valuation of observations and thus better understanding of significance of observations (Case et al., 1999; **?**). However, as found by (Bar-Hillel, 1980), base rates are weighted lower than relevant information about a subject. Casscells et al. (1978) demonstrated that clinicians ignore the base rate of a rare disease if patients present data which strongly suggests the presence of the disease. Therefore, extension neglect and base rate neglect are of high risk in resource-rich scenarios. Note that this may be a desirable case: Koehler (1996) states that highly diagnostic information should have a greater impact on decisions than base rates. |

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