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Clinical experience as evidence in evidence-based practice

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Background. This paper's starting point is the recognition (descriptive not normative) that, for the vast majority of day-to-day clinical decision-making situations, the 'evidence' for decision-making is experiential knowledge. Moreover, reliance on this knowledge base means that nurses must use cognitive shortcuts or heuristics for handling information when making decisions. These heuristics encourage systematic biases in decision-makers and deviations from the normative rules of 'good' decision-making.

Aims. The aim of the paper is to explore three common heuristics and the biases that arise when handling complex information in clinical decision-making (overconfidence, hindsight and base rate neglect) and, in response to these biases, to illustrate some simple techniques for reducing the negative influence of heuristics.

Discussion. Nurses face a limited range of types of uncertainty in their clinical decisions and draw primarily on experiential knowledge to handle these uncertainties. This paper argues that experiential knowledge is a necessary but not sufficient basis for clinical decision-making. It illustrates how overconfidence in one's knowledge base, being correct 'after the event' or with the benefit of hindsight, and ignoring the base rates associated with events, conditions or health states, can impact on professional judgements and decisions. The paper illustrates some simple strategies for minimizing the impact of heuristics on the real-life clinical decisions of nurses.

Conclusion. The paper concludes that more research knowledge of the impact of heuristics and techniques to combat them in nursing decisions is needed.

Keywords: decision-making, clinical judgement, heuristics, bias, evidence-based nursing, clinical uncertainty

Introduction

Clinical decisions and the processes that underpin them are an integral part of the delivery of health care. It is clinical decisions that commit scarce resources to patients, determine the clinical outcomes associated with care and, in part, shape the health care experience for patients and professionals alike. It is also in the realm of clinical decision-making that clinical uncertainty presents itself. In fact, medicine has been described as the 'art of making decisions without adequate information' (Sox *et al.* 1988, p. 17). Whilst derived from medicine, this definition could just as easily apply to some aspects of nursing.

Surprisingly, despite the importance of clinical decisions, very little is known about the kinds of uncertainties that health care professionals, and nurses in particular, face. One way of expressing these uncertainties – and the information needs of professionals that arise as a result – is by examining the clinical questions that nurses ask in making their clinical decisions. Ely *et al.* (1999) examined the kinds of questions that doctors ask and found that a typology of only five categories captured the range of *types* of uncertainty

Table 1 The decision types and focused clinical questions of acute care nurses in the UK (McCaughan 2002)

Decision type	Exemplar decision	Exemplar question
Intervention/effectiveness: These kinds of decisions involved choosing between intervention	Choosing a mattress for a frail elderly man on who has been admitted with an acute bowel obstruction	In elderly and inactive patients, who may require surgical intervention, which is the most suitable pressure relieving mattress to prevent pressure sores?
Targeting: this is, strictly speaking, a subcategory of intervention/effectiveness decisions outlined above. These decisions were of the form, 'choosing which patient will most benefit from the intervention'	Deciding which patients should get anti-embolic stockings	Is there a risk assessment tool available that will accurately predict which group of patients will benefit most from anti-embolic stockings?
Timing: again, a subcategory of intervention/effectiveness decisions. These commonly take the form of choosing the best time to deploy the intervention	Choosing a time to commence asthma education on newly diagnosed asthmatics	When to commence asthma education on newly diagnosed asthmatics?
Communication: these kinds of decisions commonly focus on choices relating to ways of delivering and receiving information to and from patients, families or colleagues. Sometimes these decisions are specifically related to the communication of risks and benefits of different interventions or prognostic categories	Choosing how to approach cardiac rehabilitation with an elderly patient following acute myocardial infarction who lives alone with their family nearby	Would I be better talking and explaining rehab with the patient's family present so that a clear understanding is obtained prior to the patient's discharge?
Service organization, delivery and management: these kinds of decisions concern the configuration or processes of service delivery	Choosing how to organize handover so that communication is most effective	How should I organize handover so that the most effective form of communicating information results?
Experiential, understanding or hermeneutic: these relate to the interpretation of cues in the process of care	Choosing how to reassure a patient who is worrying about cardiac arrest after witnessing another patient arresting	How best do you reassure a patient who has witnessed someone having a cardiac arrest?

encountered: diagnosis, treatment, management, epidemiology and non-clinical questions. The team of researchers to which I belong at York has found that a taxonomy of six categories captures the range of decision-based uncertainties facing acute care nurses (McCaughan 2002): intervention, timing, targeting, communication, service delivery and organization, and hermeneutic or experiential (see Table 1).

In examining the ways in which nurses access information as a response to these uncertainties (Thompson *et al.* 2001a) and their perceptions of the information's usefulness in reducing the uncertainties associated with clinical decisions (Thompson *et al.* 2001b), we have found that most rely heavily on experience to meet the information needs associated with decision choices under conditions of uncertainty. This reliance on experience – either their own or the combined experience of others – raises the obvious question of whether experience is a *sufficient* basis for reliable clinical decision-making. Specifically, does experience reduce the chances of error or poor decision outcomes?

Of course, even where nurses may wish to make use of research knowledge, as opposed to tacit self-knowledge or the orally transferred knowledge of colleagues, it is sometimes difficult to do so. They may lack the necessary computer and searching skills to access research information effectively and efficiently; not have the necessary hardware or software in the care environment; lack the critical appraisal skills necessary to interpret research findings for validity, clinical importance and applicability; and they may have to operate in an organizational environment which is not conducive to implementing research or evidence-based change.

Evidence-based practice: a working definition

Commentators have chosen to interpret the central tenets of evidence-based health care differently. For the sake of clarity, and because this paper has a nursing focus, I shall adopt the definition proposed by DiCenso *et al.* (1998). Evidence-based nursing is a process by which nurses make clinical decisions using the best available research evidence, their clinical expertise and patient preferences, in the context of available resources. Evidence-based nursing is designed to be a systematic means of combating the biases that arise from uninformed (by research evidence) decision-making. It does this by steering clinicians towards the *best* form of research evidence, given the kind of clinical uncertainty they face. 'Best' in this context means research based on a design most likely to lead to valid and reliable results and reduce the uncertainties that led to seeking information in the first place. These best designs are sometimes referred to as hierarchies of evidence. For example, for clinical decisions involving selecting a treatment or intervention from a discrete range of choices, then systematic reviews of good quality randomized controlled trials are usually considered the most valid and reliable research designs, non-randomized controlled studies less so, and non-controlled cohort designs even less than that. The least reliable and valid form of evidence, however, is always professional opinion when used *on its own*. Nevertheless, evidence it is, and nurses appear to place a higher value on it for decision-making than any other source of information available in practice (Thompson *et al.* 2001b). Proponents of evidence-based practice may not like this picture (and certainly I agree with them) but the problem for clinicians – and researchers studying them – is how to make good quality decisions when primarily drawing on experiential knowledge.

The problem

The field of cognitive science has generated many answers to the problem of how people should make decisions under conditions of uncertainty. Some examples of these normative 'decision rules' are: use objective probabilities, avoid using hindsight knowledge, choose the option with the largest expected gain and smallest expected loss, and be aware of the effect of the ways in which decision choices are 'framed'. The problem is that people consistently fail to adhere to such normative models of behaviour in real life decision-making. In order to understand decision models it is necessary to understand the idea of probabilities.

Subjective probabilities

In their pure, unadulterated state probabilities represent chance, or a numeric measure of the uncertainty associated with an event or events. Like other forms of numbers they have complex properties – they can be added, multiplied and combined in various ways. Probabilities range from 0 (representing complete uncertainty) to 1 (representing complete certainty). For example, in research reports the shorthand $P = 0.05$ means there is 5% probability that the event observed happened by chance. Of course, people rarely use probabilities in this pure form in real life. Instead, they prefer to express probabilities as odds (such as a '1000 to 1' chance) or as percentages (there's a 35% chance). Even more likely in health care is the expression of probabilities in qualitative terms: 'there's a good chance that wound dressing X will improve your pressure ulcer more than wound dressing Y' or 'it is much *more likely* to be disease A than disease B'.

So individuals fail to use probabilities in their objective sense and, even where they do, they fail to follow the rules for combining them properly (Robinson & Hastie 1985). Moreover, for the messy and complex decisions of clinical practice, they make use of a series of cognitive shortcuts called heuristics. These heuristics, and their use by clinicians, have been well documented both in medicine (Christensen-Szalanski & Bushyhead 1981) and amongst midwives (Cioffi 1997). Heuristics, whilst useful and necessary, have one unfortunate characteristic: they introduce a series of systematic biases into decisions. It is these biases and possible ways of combating them that are the focus of this paper.

Of course, one way of combating the biases arising from subjective probabilities and use of heuristics is to make use of research knowledge in decision processes. Good quality research knowledge combats the sorts of biases associated with the generation of subjective probabilities by using data collection and analytic techniques designed to minimize the chances of introducing systematic errors into conclusions. However, research knowledge is not always available or, as already highlighted, some individuals may lack the knowledge and skills to make use of it in meaningful ways.

This situation represents something of a dilemma, in that the decisions we make as professionals often merit the use of research-based knowledge. However, that knowledge is frequently not available in a format we can readily use. Yet we want to make the best possible decisions for our patients. Fortunately, despite the presence and impact of heuristics, there are techniques that individuals can be applied and which serve to confine or limit heuristic impact on decision choices. Because there are many heuristics, biases and systematic deviations from the normative rules of decision-making, I will focus on just three of the most common: overconfidence, hindsight and neglecting base rates of diseases or conditions in populations.

Real-life strategies for handling clinical decisions: heuristics, biases and some strategies for improvement

Overconfidence

Individuals often overestimate the 'correctness' of their knowledge, and a number of definitive studies have shown that people are often overconfident when it comes to decision-making or judgement tasks (Fischoff & MacGregor 1975, Lichenstein & Fischoff 1977). Overconfidence occurs at many levels, but two of the most common are as a response to knowledge questions and in subjectively predicting the progress of events or individuals. The Nottingham University Behavioural Sciences team have produced a series of exercises (available at http://www.nottingham.ac.uk/~mczwww/tltp/decis.htm) which graphically demonstrate how reliance on your own sense of confidence – even when applied to a range of answers rather than point estimates, and where you only need to be 90% sure – can be hopelessly inaccurate. Dawes (1979) examined the subjective predictions of clinicians about the outcomes of people with mental health problems and found that these were far less accurate and consistent than judgements made using objective indicators or measures of progress. Clearly, such overconfidence has implications for treatment or management decisions based primarily on experientially-informed judgement.

Combating overconfidence

The ability to know what you do not know and revise estimates of correctness accordingly is referred to as calibration and is the key to combating the bias introduced by overconfidence. There are a variety of techniques for increasing calibration.

Firstly, one of the reasons people appear overconfident in new situations is that they rely on estimates of the probability of the *area* rather than use their *detailed* knowledge of the question asked or decision task faced. By avoiding predictions in unfamiliar domains, we can combat this.

Another simple way of combating overconfidence is by consciously adjusting your own personal confidence estimates downwards. So, for example, if in the face of an uncertain decision choice you believe that you are 90% sure that decision option A is the correct choice, then try asking yourself if you would still make the same choice based on the fact that you are only 75% sure. One way of forcing yourself to revisit your personal confidence limits is to think of reasons why you might be wrong or to try to falsify the assumptions that underpin your decision choice.

Feedback on decisions can be a powerful means of combating overconfidence. Lichenstein and Fischoff (1980) demonstrated that students who received reports and explanations of results tended toward under- rather than overconfidence on a one-sided probability 'rating of correctness' scale for two-choice knowledge questions. For a less academic and more accessible example, consider the good performance (on average) of weather forecasters. The reason why they are so calibrated is that they receive continuous feedback on the justification of their confidence levels.

The following clinical example illustrates what such calibration and feedback might look like. Imagine that you are a staff nurse working on a day surgery unit. You have an informal analgesia protocol that you apply to most of your patients with hernia repairs because you are fairly confident (based on a couple of years' experience) that it works and that patients get a few hours relatively pain-free at home after they have left the unit. However, you have not really stopped to consider whether there are better alternatives, and you realize that you receive no feedback on whether the pain relief carries on working in the hours after discharge. You decide that if the pain relief was not effective after discharge then you would – in all probability – try and devise something better. You decide to 'test' whether your confidence is justified. You arrange for one of your colleagues or yourself to administer a pain measurement scale to each patient before leaving the ward and then phone them within 6 hours of discharge and simply ask them to complete it again and send it back. The findings surprise you, and you realize that in fact a large proportion of patients' pain is not well managed by the protocol after discharge. Obviously, you would not have received this information if you had not sought feedback on your initial decision choice. Clearly, you now have a solid footing for a more evidence-based approach to revision of the pain relief protocol, and repeat the 'decision audit' at a later date to see if this has worked.

Hindsight

When asked to predict an event in advance, people who know that such an event actually occurs assign higher probabilities of it occurring than those who did not know that the event occurs (Fischoff 1975). This phenomenon – called hindsight bias – can lead to people changing the relative importance of influences that their judgement tells them are responsible for an event. In short, knowing the outcome of an event makes subsequent similar outcomes more likely. Arkes *et al.* (1981) demonstrated that physicians who knew the correct diagnoses for a series of medical conditions were more likely to assign a higher probability to those diagnoses after the event. These findings have a number of important implications. First, when confronted with *a priori* knowledge of an event, clinicians attempt to make sense of what they know has happened, rather than working with objective data. The implications of this for nurses (particularly expert nurses) can be seen in the popularity of teaching diagnosis using real clinical cases in the clinical environment. Nurses should always work prospectively from diagnostic work-up to prognostic or treatment decisions, rather than working backwards from diagnosis. If they already know the diagnosis, then it is likely that they will 'see' the appropriate clinical cues. It is far better that they should work *from* clinical cues *to* the diagnosis. Arkes *et al.* (1981) have demonstrated this effect in medicine. They showed 15 physicians a case history accompanied by laboratory test results, and asked them to provide probabilities for four different (but possible) diagnoses. The probabilities at this stage were 44%, 29%, 16% and 11%, respectively. Separate groups of 15 doctors were told prior to reading the case history that the diagnosis was one of the four possible options. Having this information changed the probabilities to 39%, 35%, 38% and 31%, respectively. On average, then, hindsight adds around 11% to the probability estimate of a correct diagnosis, regardless of whether the diagnosis is actually correct – note that this is an 'average' figure and includes downward shifts in estimates as well as positive revisions. There are a number of other problems associated with hindsight, including the favourable distortion of memory (Fischoff & Beyth 1975) and (rather worryingly from a researcher's perspective) undervaluing the original nature of predictive thought and ideas expressed via scientific manuscripts submitted to peer reviewed journals (Slovic & Fischoff 1977).

Combating hindsight bias

There are two very useful techniques that can directly or indirectly reduce the impact of hindsight bias on clinical decision-making. The first, challenging decision-makers or judges by instructing them to ignore hindsight, could be useful (but difficult to implement in practice) (Hasher *et al.* 1981). The second is asking professionals to provide reasons why an outcome occurred and/or get them to focus on alternative possible outcomes that may have occurred (regardless of whether they actually did or not) (Slovic & Fischoff 1977).

Base rate neglect

As nurses are increasingly asked to consider ordering (and interpreting) diagnostic tests, it is essential that they understand the importance of acknowledging base rates associated with diseases or conditions in populations. The normative rule for situations in which there are two independent probabilities of the same event (for example, the presence of a particular disease such as depression) is to combine the two independent probabilities. The independent probabilities in this case (a diagnostic decision) are the prior probability of having depression, for example, and the probability of having depression, *given* the results of a diagnostic test. This normative rule is known as Bayes' method and can be expressed as:

$$\text{Prior odds} \times \text{likelihood ratio} = \text{posterior odds}$$

The problem for decision-makers and nurse researchers is that clinicians tend to ignore or place insufficient weight on the prior probabilities (base rates) associated with conditions or phenomena – a situation known as base rate neglect. The bias this introduces into decision-making (particularly diagnostic decision-making) can have important consequences. An example will help illustrate this.

Imagine that you are a staff nurse working in a community stroke rehabilitation clinic. Your experience tells you that being depressed whilst undergoing treatment does not help the treatment to succeed: you do not eat properly, you feel lethargic and your social relationships suffer. Clearly you would like to be able accurately to detect depression in patients and instigate appropriate treatment or referrals. During a Medline search you find a paper (Passik *et al.* 2001) which suggests that the *Brief Zung Self-Rating Depression Scale (BZSDS)* can be adapted so that a score of more than 33 is a useful cut-off for diagnosing depression in practice. It is quick to administer, and in 35 patients only one false positive result was generated. The paper reports that the BZSDS has a sensitivity of 29% and a specificity of 97%. This seems satisfactory – although if you are brutally honest you are not entirely sure what this might mean for your patients.

You note that the study was conducted in oncology units and that the prevalence of moderate depression in these settings was between 15% and 25%. You cannot be sure what the prevalence would be in your clinical area, but a colleague administered the Beck Depression Inventory as part of their Master's degree research and this suggested that around 5% of your patients were moderately depressed. Looking at the paper again, you decide to follow the normative decision rule and combine the prior and likelihood probabilities associated with the results presented and see what happens to the results if the lower prevalence of depression in your patients is taken into account. Knowing this information will help you decide if the test is useful or not. There are a variety of ways of combining the probabilities, but the easiest is to construct a 2×2 table (Hunink *et al.* 2001) using the information presented in the paper. In this example, I have used a fictional cohort of 10 000 patients for ease of computation. The answers are the same if more reasonable clinical numbers are used.

Using the method is a four-stage process, as outlined in Table 2. The final 'positive test' row (i.e. for those patients who have a BZSDS of more than 33) shows that the post-test probability (for a pretest probability, i.e. base rate, of 25%) of actually having depression given a positive test score is

Table 2 The steps in probability revision for the Zung Brief Self-Report Depression Scale (ZBSD) for diagnosing depression (oncology patients)

ZBSD result	Depression	No depression	Total by row
Step 1: use prevalence to fix column totals: 25% × 10 000 = 2500			
Positive (> 33)			
Negative (< 33)			
Total by column	2500	7500	10 000
Step 2: use sensitivity to fill in disease column: 29% × 2500 = 725			
Positive (> 33)	725		
Negative (< 33)	1775		
Total by column	2500	7500	10 000
Step 3: use specificity to fill in non-disease column: 97% × 7500 = 7275			
Positive (> 33)	725	225	
Negative (< 33)	1775	7275	
Total by column	2500	7500	10 000
Step 4: compute row totals: 725 + 225 = 950			
Positive (> 33)	725	225	950
Negative (< 33)	1775	7275	9050
Total by column	2500	7500	10 000

76% (725/950). Therefore, as a tool for identifying depression in oncology patients, the BZSDS appears quite useful. But what happens to the utility of the test when the 'real world' prevalence of 5% (i.e. the base rate of depression in your patients) is inserted into the table? Table 3 demonstrates the impact of the lower base rate.

What Table 3 shows is that, of 430 patients who would be expected to have a positive test result, only 145 actually have depression. So the post-test probability of having depression is only 33% (given a pretest probability of 5%). In this case, and for your patients, perhaps the test is not quite as useful an aid to diagnosing depression.

A number of studies have found that in the laboratory clinicians (like all humans) are poor at taking into account base rates (Casscells *et al.* 1978, Fischoff *et al.* 1979). However, Christensen-Szalanski and Bushyhead (1981) suggest that, when clinicians are encouraged to draw on experience to generate base rates, their use more closely approximates the normatively 'correct' way of combining probabilities. As far as I am aware, little research into the ways in which nurses use diagnostic probabilities has been conducted. However, the work of Offredy (2002) shows that nurses do not appear to revise probabilities or adjust diagnostic strategies for different base rates, even when

Table 3 The steps in probability revision for the Zung Brief Self-Report Depression Scale (ZBSD) For Diagnosing Depression (community based stroke rehabilitation Patients)

ZBSD result	Depression	No depression	Total by row
Step 1: use prevalence to fix column totals: 5% × 10 000 = 500			
Positive (> 33)			
Negative (< 33)			
Total by column	500	9500	10 000
Step 2: use sensitivity to fill in disease column: 29% × 500 = 145			
Positive (> 33)	145		
Negative (< 33)	355		
Total by column	500	9500	10 000
Step 3: use specificity to fill in non-disease column: 97% × 9500 = 9215			
Positive (> 33)	145	285	
Negative (< 33)	355	9215	
Total by column	500	9500	10 000
Step 4: compute row totals: 145 + 285 = 430			
Positive (> 33)	145	285	430
Negative (< 33)	355	9215	9570
Total by column	500	9500	10 000

What is already known about this topic

- Evidence-based practice relies in part on the application of normative decision rules that in turn rely on clinicians making use of probabilities, both objective and subjective.
- Health care professionals use cognitive shortcuts (heuristics) in order to make sense of the information that surrounds clinical decisions and this can lead to systematic errors in health care decision making.

What this paper adds

- Discusses the application of three common heuristics in nursing practice.
- Illustrates some possible (but partial) solutions to the mismatch between normative and real-world decision making.
- Suggests agenda items for nurse researchers and educationalists in the area of evidence-based decision making.

qualitatively 'rare' or 'common' conditions are presented as decision tasks.

Combating base rate neglect

Theoretically, the simplest way of encouraging nurses to acknowledge base rates is to teach them how to use them in their decision-making. However, from personal experience and discussion with other academics, I am unsure how many nurses are taught the relatively simple techniques illustrated above for using probabilistic information correctly. More use could be made of local prevalence audits, such as those conducted in relation to pressure area and chronic wound care. Specifically, when local prevalence is taken into account, the results of the multitude of pressure risk assessment scales can become pretty meaningless. For example, in one study the Waterlow scale wrongly classified 72 of 185 patients as 'at risk' from pressure ulcers (Chan *et al.* 1997). Even very sensitive and specific tests will produce a large proportion of false positives when the prevalence of the disease or condition is exceedingly low. The influences of base rates have obvious implications for the role of nurses in mass screening for rare conditions. One example here might be the number of false positive arising from universal newborn hearing screening, which is associated with 25–50 false positives for every true case of hearing impairment (Wessex Universal Neonatal Hearing Screening Trial Group 1998).

Conclusion and a caveat

I have drawn attention to the fact that most nurses draw on experience and experiential knowledge as the prime sources of evidence for most day-to-day clinical decisions that they encounter. Whilst I am a strong advocate of evidence-based practice (in its 'classical' format), I am forced to concede that in many instances the evidence used in clinical decision-making is not always good quality research knowledge able to be critically appraised for validity, clinical significance and applicability. With this reliance on experiential knowledge and intuitive modes of decision-making comes a commensurate reliance on cognitive shortcuts or heuristics in handling knowledge for decision-making. These entirely necessary heuristics introduce systematic biases into decisions and deviations from the normative rules of 'good' decision-making.

The paper draws attention to three common heuristics and biases: overconfidence, hindsight and base rate neglect. Of course, there are many more heuristics and biases than can be described in one short paper (for example, anchoring, availability and ignoring the expected utility of interventions). Alongside these examples I have also presented some strategies for theoretically minimizing their impact on the real-life clinical decisions of nurses. The aim of doing so is not to encourage clinicians to adopt these strategies in a wholesale and uncritical fashion, but rather to encourage debate on how we might research these concepts and processes in nursing. If we are serious about improving the decisions and judgements of nurses, then only by exposing our limitations (and indeed strengths) can we begin to design solutions.

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