Using social judgement theory to model nurses’ use of clinical information in critical care education

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Summary Understanding the learning needs of students is a vital step in planning the delivery of effective education. Evaluating the impact of such interventions is not always easy and many methods rely on self-reported behaviour or simple changes in knowledge — whose relationship to action is not always clear. Using conjoint analysis, within the theoretical framework of social judgement theory, this study illustrates a novel means of examining nurses’ use of clinical information when diagnosing hypovolemic shock in a series of simulated cases presented via computer. The study examines changes in information usage before and after a traditional lecture. The results show that nurses’ information use is not linear and the utility for decision judgement derived from clinical information is not distributed equally. The study also suggests that some clinical information (for example, the Glasgow Coma Score) is not well understood and incorporated into clinical judgement. The study has implications for those designing and evaluating educational interventions and those studying information use, clinical judgement and decision making.

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Introduction

Educational interventions are increasingly expected to be demonstrably effective and to make use of the full range of innovative technologies available. In this paper we outline an innovative approach to identifying the learning needs of nurses faced with the challenging educational experience of critical care. In addition, we illustrate a means of evaluating the impact of one educational intervention aimed at preparing them for this challenge. The principles of social judgement theory (SJT) and the associated idea of the Lens Model of human cognition and information use...
form the basis for this paper (Hammond et al., 1964).

Background

At the heart of modern professional clinical practice are nurses as 'knowledgeable doers' (Department of Health, 1999) exercising their clinical judgement in the context of evidence based decisions made for the benefit of patients (Royal College of Nursing, 2003). Evidence based decisions involve successfully combining information from research knowledge, with knowledge of available resources, clinical expertise and the patients’ preferences (DiCenso et al., 1998). However, little is known about how nurses integrate (successfully or otherwise) these sources of information in the context of clinical judgements. Critical care is one key environment in which nurses face judgement tasks in which their associated clinical decisions have important implications for patients (Bucknall and Thomas, 1997) (Department of Health, 2001b).

In the United Kingdom, recent policy drivers have created a unique opportunity for nurse educators to contribute to the need for nurses to enter the workforce with some knowledge and skills in critical care (Department of Health, 1999, 2001a). It has been estimated that up to 80% of in-hospital cardiac arrests are predictable (UK Resuscitation Council, 2000). This highlights the need for nursing staff to be equipped with the necessary skills for recognising the 'at risk' patient and intervening before potentially life threatening events.

Social judgement theory and the lens model of cognition

The theoretical basis for the study is the ‘lens model’ proposed by Brunswik and later utilised by Hammond et al. (1964). The model can be represented graphically (Fig. 1).

The left side of the model represents a real situation (in this case a patient’s diagnosis of hypovolemic shock for example). This is known as the judgement ‘ecology’. A variety of pieces of clinical information – known as cues – are correlated with this side of the model (for example, the clinical signs and symptoms of hypovolemic shock). Each cue has a weight and contributes to the ecology. This contribution can be captured statistically using regression modelling techniques.

Of course, clinicians will also attach importance to cues in making a clinical decision; this is captured by the right side of the model. These may or may not be similar to the weights associated with the true (ecological) state. Again, using regression modelling clinicians’ weights can be measured.

Exploring how well clinicians unite the left and right side of the models in their clinical judgements helps us predict the accuracy of judgements, the weights of the information cues involved, and the variability within and between clinicians. Consequently, the application of the lens model has the potential to provide baseline data for use in the design and evaluation of interventions to improve clinical judgements for a given judgement task.

The rationale for the lens model stems from Brunswik’s ideas on probabilistic functionalism in which he postulated that the relationship between an individual and their environment was based on the edict that nothing in life is certain and that environmental variables (such as clinical signs and symptoms and eventual diagnosis) are only ever probabilistically related (Cooksey, 1996). It was primarily the work of Hammond et al. (1964) that extended Brunswik’s ideas into the domain of human judgement. Specifically, using the concept of the cognitive continuum, he argued that the complexity of the ecology’s structure, the numbers of cues present, and the time available for exercising judgement will dictate what kinds of information and processing will be required to perform the task successfully. Consequently, there is value in knowledge of both the task and the information-based responses to that task.

Social judgement approaches have been used to model diagnostic ability in clinicians (Wigton et al., 1986), to examine prioritisation decisions by
occupational therapists (Harries, 2002), and to examine the predictive abilities of psychiatrists and mental health nurses with patients at risk of suicide (Dowding, in progress, Scottish Chief Scientists Office grant CSO IC2H/4/36).

The social and hidden nature of clinical judgements

It may seem paradoxical to conceptualise what is often assumed to be a lone activity — clinical judgement — as social. However, where nurses (and other healthcare professionals) are confronted by uncertainty in clinical practice the information source most often consulted is another colleague or professional (Thompson et al., 2001; Covell et al., 1985; Gorman and Helfand, 1995; Gorman, 1999). Yates and colleagues argue that judgements are social in the sense:

...that different individuals faced with the same judgement tasks often disagree in their predictions... social judgement theory methods provide a means for explaining such disagreements in terms of the parties’ different implicit assumptions about the ecology (e.g., about cue validities) and how they go about the judgement task (e.g., the emphases they put on particular cues and how reliably they execute their judgement policies).

(Yates et al., 2003)

One difficulty with using the judgements of nurses as the basis for developing and evaluating educational interventions is that conventional methods exploring such choices often produce little in the way of detailed understanding and often involve the use of subject recall of judgements already made. Relying solely on hindsight has the potential for introducing bias (Kahneman and Tversky, 1973). Methods such as “think aloud” are often predicated on the respondent’s ability to verbalise their judgements and the information being considered. However, the cues that may actually influence people may not be the cues that are reported. Social judgement models recognise that cues are often difficult to verbalise, and (in clinical practice) often correlated with each other — for example, the relationship between blood pressure and pulse in hypovolemic shock.

Being able to develop predictive models of the relationship between judgement task and the information used in performing the task is an important activity in critical care. Small changes in a patient’s clinical signs and symptoms (the information cues in the modelling exercise) can have significant effects on morbidity and mortality.

Mapping the ways in which information is actually used in relation to real judgement tasks faced may help those designing and evaluating decision support systems. Currently many models of decision support (particularly computerised decision support are based on normative models of decision making (the example being systems based on Bayesian approaches to unifying prior and posterior probabilities). Indeed given the complexity of interventions to support decision making such descriptive and theoretical modelling is essential (Medical Research Council, 2000).

Methods

Design

The study was only intended to ascertain the feasibility of a much larger piece of work. Because of the lack of need to be able to generalise a quasi-experimental single group pre-test, post-test design was used (Cook and Campbell, 1979). As (at this stage) we had no suitable data-set to calculate the ecological cue weights, we were concerned with populating the right hand side of the model (nurses’ relationship to the judgement task and use of information). The exercise was conducted in a computer laboratory at the University of York in a single day in February 2003. Given the limited scale of the project and its pilot status, ethical approval was sought (and gained) from our internal departmental ethics committee Chair.

Participants

Twenty-three 2nd year UK student nurses undertaking a level 3 (degree level) educational module on critical care. The average age was 34 years (SD 9.32); 26% (6) had 5 or more GCSE passes or above, 17% (4) A levels, diploma or other educational awards, 13% had vocational qualifications and 9% (2) were graduates on entry to nursing.

Procedure

The reason for the study was explained to the students as, ‘we are interested in the ways that students make use of clinical information in decision making’. Students were provided with an Internet address and asked to follow the instructions provided on-line. Two of the researchers (CT and AF)
were available to answer any additional technical queries students raised but not to intervene with interpretation of clinical data presented. They were told that the procedure would take anywhere from 15 to 25 min to complete. The time taken till last student completion was 26 min. It was pointed out to the students that they did not have to participate if they did not wish. Two students declined to participate.

Following completion of the pre-test judgement task students were given a traditional didactic lecture on the principles and practice of dealing with patients in shock. The lecture made explicit reference to the clinical signs and symptoms used in the social judgement model.

Thirty minutes after the lecture students came back to the computer laboratory and retook the judgement test. The time taken till last student completion was 24 min.

Judgement policy capture approach

A conjoint analytic approach to capturing judgement policy was used. This approach has been used previously with doctors to examine their information use when diagnosing pulmonary embolism (Wigton et al., 1986). The Statistical Package for the Social Sciences (SPSS) version 10 and the additional SPSS conjoint module were used.

Six pieces of clinical information — pulse, respiratory rate, systolic blood pressure, urine output per hour, GCS, and oxygen saturation — were selected as important for diagnosing shock by three clinicians with extensive experience in critical care settings. Each of the pieces of information was represented at 3 levels of abnormality: normal, equivocal, or abnormal. In order that as much ecological validity as possible was retained we presented the data in the manner that nurses would encounter it in practice (for example, a systolic blood pressure of 86 would be a ‘normal’ value), rather than interpreted for them as ‘abnormal’, ‘normal’ or ‘equivocal’. A fractional factorial design was designed to capture the main effects in the model by using the SPSS Orthoplan procedure. The 6 (factors) \( \times 3 \) (values) matrix generated a 20 card orthogonal design.

The cards in the factorial design were converted into 20 scenarios, placing the factors and levels in the context of two clinical judgement tasks:

1. estimating the likelihood that the patient is in shock;
2. providing a dichotomous judgement on whether the patient is in shock or not.

The scenarios were based around a fictitious patient (Jones) who was 59 years old and 75 kg on admission to hospital. The patient had undergone a total hip replacement and was returned to the High Dependency Unit (HDU) at 14.00 h. We provided nurses with her baseline vital signs on admission and told them that at 20.00 h Jones was complaining that she felt dizzy, sweaty and thirsty. We pointed out that she was drinking plenty of fluids pre-operatively but was nil by mouth for 10 h prior to surgery. A 1000 ml of blood had been lost in theatre and this had not been was not fully replaced. She was also described as pale and restless.

We then showed the nurses 20 sets of observations in which the data on blood pressure, pulse, respiratory rate, urine output, oxygen saturation, and GCS (Glasgow Coma Score) were manipulated according to the requirements of the factorial design. The nurses undertook the judgement tasks described above for each of the 20 scenarios viewed and judged in relation to the baseline information presented. Demographic data on the participants were also collected to enable between-group statistical comparisons at a later stage and on a larger sample of nurses.

The scenarios were presented on-line as ‘static’ HTML (web) pages. Each page had an input box and a yes/no response ‘button’. Student responses to the judgement tasks were captured via a Coldfusion application written for the project by the lead researcher (CT). The responses were written to a password-protected database. The contents of the database were cut and pasted directly into SPSS. The Coldfusion application can be viewed at [http://www.york.ac.uk/res/dec/shock/](http://www.york.ac.uk/res/dec/shock/).

Analysis

The lens model formed the overall conceptual basis for the study but the analysis made use of conjoint analysis (Green and Rao, 1971) to generate the weightings assigned to the clinical information by students. Conjoint analysis has been used in a variety of ways in healthcare settings (Orkin and Greenhow, 1978; Richardson et al., 1984) but is most often employed to examine consumer preferences for product or service attributes (Ryan and Farrar, 2000). Conjoint analysis is a form of regression and the underlying model for our study (using just 2 clinical factors as an example was) was:

\[
U(x) = b_0 + b_1(x_{11}) + b_2(x_{12}) + b_3(x_{13}) + b_4(x_{21}) \\
+ b_5(x_{22}) + b_6(x_{23}) + e,
\]
where $e$ is the error term; $U$ is the overall utility; $b_1, b_2, \ldots, b_6$ are the coefficients for each value (1, 2, 3) for each clinical factor (1,2); $b_0$ is the utility when all factors are at level 0 (the first level). The contribution each clinical factor makes to the overall utility (e.g., $b_1(x_{12})$) is termed the part worth. Because we used dummy variable analysis (e.g., levels 0, 1, 2) the part worth is equal to the coefficient $b$.

The results generated from this analysis include the relative utility of each clinical factor at each of its levels (known as part worths or conjoint utilities). These results allow for the examination of linearity in response and, as the categories of normal, equivocal and abnormal were ordinal data, whether there were plateau or threshold effects associated with information use. It is also possible to calculate the difference each clinical factor makes to the total utility associated with a judgement. Importance data are ratio data and so if urine output has an importance of 20 and GCS has an importance of 10, then information on urine output makes twice the contribution to the judgement as GCS.

**Results**

There are a number of ways in which the results of the study can be used. First, we could have used the results to tailor the information imparted during the lecture to the needs of the students. Alternatively — and as was the primary use in the pilot — we could use the results to provide an evaluation of the impact of the lecture.

**Variable judgements despite same information**

Despite being presented with identical information in the scenarios, there was little consensus in either the estimates of likelihood or the (dichotomous) judgement of whether the patient was in shock or not. The large standard deviations in Table 1 are illustrative of the range of likelihood estimates. The table also highlights that, with the exception of scenario 20, there was always at least 10% of disagreement between the nurses regarding the patient’s haemodynamic status.

**What clinical factors are important for student nurses diagnosing shock?**

Taking the utility range for the clinical factor and dividing it by the sum of all the utility ranges compute factor importance. As can be seen from Table 2 prior to the lecture nurses attached similar levels of importance to each of the clinical factors — with the exception of the GCS. How-

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Table 1 Estimated mean likelihood of shock and dichotomous judgement by nurses by scenario pre- and post-educational intervention
ever, following the lecture respiratory rate is clearly the most important clinical factor for the students as a whole. However this summary picture masks the considerable variation in the importance attached to clinical factors within the group. Fig. 2 illustrates the pre- and post-lecture variation in importance when each individual's judgement is examined. The graphs illustrate that intra group variation does not appear to diminish after the lecture. On a larger sample of nurses it would be possible to test this hypothesis using inferential statistics.

The impact of the lecture

Figs. 3 and 4 show the results of examining the pre- and post-utilities for each of the factors at each of the 3 levels of abnormalities. The small numbers of students involved in the study make such comparisons purely descriptive. These utilities could be used as dependent variables in regression modelling in suitably powered studies. However, visual inspection of the results suggests little, clinically significant change in the ways that information is used.

### Does level of clinical information make a difference?

A prime reason for using social judgement approaches to examining the use of information by clinicians is to establish the relative contribution to judgement of differing levels of information. By examining the part worths (utilities) associated with the nurses involved some important findings are revealed. Figs. 3 and 4 show that BP, pulse, respiratory rate and oxygen saturation had a linear relationship with the judged outcome, both pre- and post-lecture. Nurses’ use of Information on urine output appears to exhibit a threshold effect. Nurses used equivocal information on urine output in the same way as information suggesting a normal output: very little utility is gained. Information suggesting an abnormal urine output resulted in a change in the degree of utility and a much higher level of positive part worth. Figs. 3 and 4 also show that nurses gained very little utility at all from information on the GCS and that this pattern did not alter after the lecture.
As with the importance associated with the clinical factors at the group level (Table 2) these summary utilities mask the considerable variation in the utilities that individual nurses derive from the clinical information at various levels of abnormality. Fig. 5 presents the part worths for the clinical factor GCS when it is abnormal and nurses are grouped by level of educational attainment on entry to nursing. Once again the spread of utilities suggests different usage of the information in clinician’s judgement policies.

**Discussion**

Despite its previous lack of application to nursing, using social judgement approaches to the planning
and evaluation of nurse educational interventions is a real possibility. Contemporary educational discourse around the training of healthcare professionals emphasises the role of ‘learner centred’ (Sackett et al., 2000) approaches and targeted interventions as means of changing knowledge and practice (NHS Centre for Reviews and Dissemination, 1999). Our results suggest that it is possible to construct deconstruct the information use underpinning the judgements and decisions associated with practice.

Similarly, social judgement approaches have utility as tools for evaluating educational interventions. Many evaluations of educational interventions simply focus on changes in knowledge rather than practice. Whilst SJT does not directly observe changes in practice it does evaluate changes in real judgements and choices (albeit in response to simulated cases). Using simulated cases is methodologically challenging (Lamond et al., 1996), but we would argue that the approach has greater validity than relying on self reported choices — with the potential for hindsight bias that this entails (Lichenstein et al., 1982). The results of the small piece of developmental work reported in this study provide not only an estimate of the impact of an intervention, but also as a source of explanation for any impact observed. Success in judgement tasks is largely context dependent (Lamond et al., 1996) and we would argue that SJT provides greater opportunities for retaining ecological context than alternative methods.

The approach outlined in this paper suggests that information use is not necessarily linear or even in the direction expected. SJT approaches reveal this complexity, which would be lost if we used group-averaged learning needs as a start point for planning or evaluating teaching and learning. Moreover, whilst not outlined in this paper — SJT allows for the development of predictive models, validation and reference to real ecologies as means of adding increased value to the analysis. Two of the authors of this paper (CT and DD) are currently exploring ways of mapping the ecologies associated with judgement tasks in both critical care and suicide prevention. This will enable comparison between the left and right side of the judgement model and an assessment of how well nurses’ information use matches the ecology of common judgement tasks.

Limitations of the approach

As with any single-group pre-post-test quasi experimental study there are some significant threats to validity (Cook and Campbell, 1979). Pre-post designs are always susceptible to the danger that history intervenes in the observed effect as a result of events apart from the

Figure 5 Utilities for GCS post-lecture by individual (grouped by level of educational attainment on entry to nursing).
intervention happening between measures. Similarly, the repeated measures design of the evaluation means that maturation, or developments in the group between measurements, is a possibility. It is possible that the group we observed were somehow more “in need” of education than others and that statistical regression to the mean might have led to an unwarranted conclusion of (in) effectiveness. The half hour window after the intervention and before measurement meant minimal opportunity for history or maturation to impact on analysis. Admittedly, without a control group it is difficult to know whether the group differed from similar cohorts. The small number of non-randomly selected students in the study prevented the use of inferential statistics with consequent limitations on generalisability. However, such generalisations were not the purpose of the paper. Within SJT and conjoint approaches there is a necessary trade off between promoting the maximum ecological validity and the time taken to undertake the exercise. The number of clinical factors and levels is dictated in part by the endurance of the subjects. Our use of fractional factorial designs in scenario construction maximised the effects observed without substantive loss of information.

Conclusion

Conjoint and social judgement analytic approaches are a potentially valuable way of planning and evaluating educational interventions for nurses. The approach illustrates the variability in judgements and choices made by clinicians but also provides valuable information on the sources of this variability. Despite the theoretical benefits of the approach, more research is required in educational and practice settings to establish the validity of the approach and its utility for educators and practice developers.

References


Available online at www.sciencedirect.com